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The Dynamic Nature of Physical Activity Intentions: A Within-Person Perspective on Intention-Behavior Coupling

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Abstract

The intention-behavior gap has proven to be a vexing problem for theorists and practitioners interested in physical activity. Intention stability is one factor which moderates this gap. This study articulated and tested contrasting views of intention stability as (a) a dynamic characteristic of people that influences assessment error (and therefore the predictive power of intentions), and (b) the product of a dynamic process that unfolds within people over time. Using an ecological momentary assessment design, young adults ($N = 30$) rated weekly physical activity intentions for 10 weeks and wore pedometers for the first 4 weeks of the study. Substantial within-person variability existed in intentions over both 4- and 10-week intervals, and this variability was not a function of time exclusively. Multilevel modeling revealed that overall intention strength (across weeks) and weekly deviations in intention strength interacted to predict weekday (but not weekend) physical activity. These findings indicate that the person and context interact to selectively couple or decouple intentions from daily physical activity.

Keywords

self-regulation; motivation; goals; planned behavior; pedometer

Behavioral intentions feature prominently in motivational explanations of health behavior, largely due to the popularity of the theory of planned behavior in exercise and health psychology (Ajzen, 1991; Montaña & Kasprzyk, 2008). Although intentions can undoubtedly influence a variety of health behaviors, the best intentions often fail to translate into desired behaviors. Physical activity is one significant health behavior which has been impacted by this intention-behavior gap (Sheeran, 2002). People regularly set physical activity goals and find themselves frustrated or disappointed by their failure to engage or

persist in physical activity. In an effort to resolve this inconsistency and enhance understanding of and control over health behaviors such as physical activity, theorists have elaborated on the self-regulatory mechanisms that connect intentions with behaviors.

The stability of intentions has emerged as a prominent moderator of the intention-behavior gap (Conner, Sheeran, Norman, & Armitage, 2000; Cooke & Sheeran, 2004). Research on physical activity intention stability has focused on between-person differences in the consistency of intentions between two occasions but has been relatively insensitive to how intentions fluctuate within-people across repeated occasions. For example, college students' are more physically active on weekdays than on weekends (Behrens & Dinger, 2003, 2005; Sisson, McClain, & Tudor-Locke, 2008) but it is unclear whether this fluctuation in activity can be explained by corresponding fluctuations in physical activity intentions. The existing emphasis on *between*-person differences has increased understanding of physical activity motivation; however, we argue that *within*-person motivational processes must also be understood to explain physical activity and bridge the intention-behavior gap. In this paper, we report an ecological momentary assessment study of behavioral intentions and physical activity designed to (1) characterize the between- and within-person variation in weekly physical activity intentions, (2) determine the extent to which weekly intentions vary as a function of time, and (3) evaluate within-person coupling of weekly intentions and physical activity.

The Theory of Planned Behavior

The theory of planned behavior (TPB; Ajzen, 1991) is one of the most well-researched theories of health behavior and the basic TPB model has extensive support in physical activity research (for reviews, see Downs & Hausenblas, 2005; Hagger, Chatzisarantis, & Biddle, 2002). According to this theory, people's intentions to be physically active are one of the most proximal influences on their subsequent physical activity. These intentions are influenced by people's explicit attitudes, subjective norms, and perceptions of behavioral control (which also has a direct effect on behavior but is theoretically more stable than intentions). Ajzen (1991) assumed that intentions "capture the motivational factors that influence a behavior" (p. 181). Unlike attitudes, subjective norms, and perceived behavioral control, which are typically treated as relatively stable individual differences, behavioral intentions are likely to shift and reflect the ebb and flow of motivation as people navigate changing constraints, goals, and interests in their daily lives.

Such fluctuations in people's intentions may help to explain the intention-behavior gap which has emerged as a major challenge confronting the TPB (Orbell & Sheeran, 1998; Sheeran, 2002). It is well-established that people can be physically active despite not forming intentions to engage in physical activity or, more vexingly, people may remain inactive despite forming intentions to engage in physical activity (e.g., Hardeman, Kinmonth, Michie, & Sutton, 2011). Several theoretical elaborations have been proposed to bridge this gap and increase the predictive power of the TPB. These involve, but are not limited to, past behavior (Norman & Smith, 1995), habit strength (Ouellette & Wood, 1998), implementation intentions (Sheeran & Orbell, 1999), and intention stability (Conner et al.,

2000). For this study, we focused on intention stability and specifically on the importance of within-person variation in physical activity intentions.

Physical Activity Intentions Change Over Time

To date, relatively few studies have sampled physical activity intentions intensively (defined here as four or more occasions). In those few studies, approximately half of the variance in intensively-sampled biweekly and monthly physical activity intentions lies between people (Scholz, Keller, & Perren, 2009; Scholz, Nagy, Schütz, & Ziegelmann, 2008). This pattern suggests that intentions reflect both (a) relatively consistent individual differences in physical activity motivation, and (b) dynamic self-regulatory processes which respond to endogenous (e.g., fatigue) and exogenous (e.g., schoolwork) changes. Although the biweekly and monthly timescales examined by Scholz and colleagues are certainly relevant, they may be too slow to capture relevant fluctuations in motivational processes. In the United States, national physical activity guidelines identify weekly goals (Physical Activity Guidelines Advisory Committee, 2008) so we focused on a weekly timescale for intentions in this study. Drawing from the work of Scholz and colleagues, we expected that approximately half of the variability in weekly physical activity intentions would vary between-people in the present study, with the remaining variability reflecting within-person changes.

In the few studies examining how intentions vary over time, findings consistently indicate a linear decrease across semi-annual, monthly, and biweekly timescales over periods ranging from 18 weeks to 3 years (Reuter, Ziegelmann, Lippke, & Schwarzer, 2009; Scholz et al., 2009; Scholz et al., 2008). Two of those studies also suggested the potential for intentions to decrease rapidly at first but then decrease more slowly over time (i.e., quadratic change; Reuter et al., 2009; Scholz et al., 2009). Although cognitive changes in risk awareness, outcome expectancies, and self-efficacy are expected to mediate changes in intention strength over time (Schwarzer, 2008), these cognitive changes do not entirely account for the observed temporal trends (Scholz et al., 2009). In addition to those cognitive changes, we suggest that the documented intention trajectories may reflect temporal processes such as reactivity to research procedures or motivational decay over time (e.g., as interest wanes) as well as non-time-structured processes such as changes in contextual constraints on motivation (e.g., competing time demands or deadlines). Characterizing changes in weekly intention is an important first step for understanding the factors that sustain or undermine motivation over time, and developing effective physical activity promotion interventions that are sensitive to temporal processes.

Scholz et al. (2008) separated changes in intentions into time-structured and non-time structured components. Time-structured variability represented the rate at which intentions changed over time (i.e., slopes in a growth curve). This variability reflected changes in the strength of motivation over time. Non-time structured variability (i.e., net within-person variability; Ram & Gerstorf, 2009) was represented by the standard deviation of person-level intentions that were detrended of time-structured variability (i.e., standard deviations were calculated based on residual variability in weekly intentions after we controlled for the linear trend over time). This variability reflected unsystematic fluctuations in the strength of

motivation, such as that produced by exogenous (e.g., competing time demands) and endogenous (e.g., illness) factors that do not vary as a function of time per se but are likely to influence a person's motivation at a given point in time. Among people training for a marathon, runners who exhibited more non-time structured variability in their monthly training intentions were less likely to attempt marathon distances at the end of their training program, presumably because they lacked robust self-regulatory skills (Scholz et al., 2008). Collectively, this evidence suggests that (1) time-structured models are insufficient for explaining the full range of within-person variability in physical activity intentions, and (2) non-time structured variability in intentions may be meaningful for predicting physical activity. Accordingly, we hypothesized that time-structured growth models would fail to adequately capture the dynamic process underlying changes in weekly physical activity intentions in our study.

The Intention-Behavior Gap as a Within-Person Phenomenon

Although between-person differences in physical activity tracks across the lifespan (i.e., more active children tend to be more active in adulthood; Telama et al., 2005), physical activity also varies within people (e.g., from weekdays to weekends; Behrens & Dinger, 2003, 2005; Sisson et al., 2008). If weekly intentions and physical activity fluctuate at different rates, the intention-behavior gap may simply reflect the selective coupling of people's intentions with their behavior at different points in time. The three studies reviewed above provide preliminary support for such within-person coupling of intentions and physical activity. First, when college students reported stronger-than-usual intentions to exercise, they also reported greater subsequent vigorous physical activity over an 18-week period (Scholz et al., 2009). Second, as runners' training volume increased over the course of an 11-month marathon training program, their intentions also increased in strength and consistency (Scholz et al., 2008). Finally, increases in orthopedic rehabilitation patients' exercise intentions were linked with increases in exercise planning which were, in turn, linked with increases in exercise behavior over three years (Reuter et al., 2009). All three of these studies relied on self-reported physical activity and this within-person coupling hypothesis needs to be tested with objective measures of physical activity. Also, none of these studies examined intentions at the weekly timescale which has been the focus of public health recommendations. The present study addressed these limitations by assessing intentions on a weekly timescale to predict objective measures of subsequent daily physical activity.

This within-person perspective on the intention-behavior gap differs from existing between-person explanations. Of all the between-person explanations for the intention-behavior gap, the intention stability explanation is most sensitive to within-person variation in intentions. Although intention stability generally refers to the consistency of intentions over time, there is some debate about the theoretical role of intention stability in the TPB. Some have proposed that it is an operant measure of intention strength, such that people exhibiting more variable intentions are thought to have "weaker" intentions to pursue a behavior of interest (Bassili, 1993; Krosnick & Petty, 1995). Others view intention stability as a moderator of intention effects with instability reducing the size of intention effects (Ajzen, 1996). From this perspective, unstable intentions involve greater assessment error than stable intentions,

and should therefore have weaker predictive relations with behavior. This perspective contrasts with our view that intentions will vary naturally within-people and embracing that variation will lead to more accurate behavioral predictions.

The most common method used to conceptualize and quantify between-person differences in intention stability involves aggregating standardized scores derived from item-level intention ratings (Conner et al., 2000). Studies using this item-level aggregation technique have found that people with the strongest and most stable intentions have the greatest subsequent physical activity (Rhodes, de Bruijn, & Matheson, 2010; Sheeran & Abraham, 2003). In another study, goal conflict moderated the intention X intention stability interaction such that relations between intentions and physical activity were strongest for people with stable intentions over the two-week period and few competing goals (Li & Chan, 2008). This measure of intention stability even mediates the effects of other variables that moderate intention-physical activity relations (e.g., past behavior, intention certainty, self-schema, anticipated regret, attitudinal control; Sheeran & Abraham, 2003). A less common method, employed when a single item has been used to assess intentions, quantifies stability as the absolute difference in responses across two occasions. In a large, representative telephone survey of health behaviors in Quebec, relations between intentions and physical activity were stronger for people with more stable intentions than for people with less stable intentions during that period (Godin et al., 2010). Both of these methods focus on intention stability as a *dynamic characteristic* that reflects individual differences in people's capacity for change (Ram & Gerstorf, 2009). In this study, we contend that intention-behavior coupling is a selective within-person phenomenon (i.e., the product of a *dynamic process*; Ram & Gerstorf, 2009).

The Present Study

To address the gaps we identified in the literature reviewed above, we designed an ecological momentary assessment study (Stone, Shiffman, Atienza, & Nebeling, 2007) and intensively assessed college students' physical activity intentions over a 10-week period using the diary method. For the first four weeks of the study, participants also wore pedometers to count their steps (ambulatory monitoring) so we could evaluate intention-behavior coupling at the within-person level. This study extended previous work on within-person intention-behavior relations by incorporating an objective assessment of physical activity over a four-week surveillance period and sampling intentions on a timescale which corresponded with public health recommendations. Our three research questions and hypotheses for the study are summarized below.

First, we sought to describe and evaluate the relative contribution of between- and within-person variability in weekly physical activity intentions. We anticipated that, consistent with research on slower timescales, weekly physical activity intentions would vary approximately equally between- and within-people. This finding would point to the importance of separating between- and within-person components of intentions when examining their relations with behavior.

Our second research question concerned the sufficiency of a linear, time-structured growth model for describing within-person variability in weekly physical activity intentions. Based on our expectation that intentions vary as a linear function of more than time alone, we hypothesized that none of these models would fully capture within-person variability in physical activity intentions (as indicated by sub-optimal model fit).

Our final research objective was to evaluate our proposal that intention-behavior relations are the product of a dynamic process which selectively couples motivation and action. In conducting this test, we controlled for individual differences in intention stability because previous research has linked this dynamic characteristic to behavior both directly and as a moderator of intention strength. Intentions were separated into between- and within-person components to accommodate the expected behavioral effects of differences in (a) the absolute strength of intentions across weeks as well as (b) the relative strength of intention deviations during a specific week (Scholz et al., 2009). We hypothesized that, when people had stronger-than-usual intentions, they would subsequently exhibit greater-than-usual physical activity. The same unmeasured daily constraints which produce the robust weekday-weekend differences in college students' physical activity may also influence motivational dynamics; therefore, weekday/weekend status was expected to moderate intention-behavior relations.

Methods

Participants

College students ($N = 33$, 58% women) participated in this study as a part of a class project; all provided informed consent and permission to use their data for research purposes. They were predominantly White/Caucasian (94%) students in their 4th year (79%), and all indicated that they were capable of performing normal physical activity. Their mean body mass index was 25.4 ($SD = 4.8$). Two participants lost their pedometers so the sample for the analyses involving step counts was 31 people.

Instruments

Intentions were assessed using two questions: "I plan to exercise regularly over the next week" and "I intend to exercise regularly over the next week" (Rhodes, Blanchard, & Matheson, 2006a; Rhodes, Blanchard, Matheson, & Coble, 2006b). Participants rated each item on a scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). The average weekly correlation between these items in this study was .94. In previous research scores from this measure have predicted physical activity (Rhodes et al., 2006a; Rhodes et al., 2006b).

Physical activity was assessed using Omron HJ-720ITC pocket pedometers. Participants were instructed to wear the pedometer on their right hip beginning when they woke up every day and only to remove the pedometer (a) before sleep, (b) if they were bathing or swimming, or (c) if they were engaged in full-contact sports which could result in damage or injury. At the end of the four-week surveillance period, step counts were downloaded from pedometers in hourly epochs. Data from the first and final day of the period were discarded because of variability in the duration that participants had access to the pedometers on those

days. The resulting dataset provided data on step counts for 27 days (648 hourly epochs/participant and 20,736 total hourly step counts in total). We abstracted these hourly data into daily data because we did not have any hypotheses about hourly variation in physical activity whereas we did have hypotheses about variability at the daily level. To estimate daily step counts, hourly step counts when participants wore their pedometer were summed, divided by the number of total hours that the pedometer was worn that day (including sleep time), and multiplied by 24. Daily data were coded as missing for the day if the pedometer was not worn for at least 12 hours (22 days of data lost from 10 people), or if a pedometer recorded fewer than 500 steps in a day (7 days of data lost from 5 people).

Participants were also given four copies of a weekly logbook pre-numbered with their identification number. The purpose of this logbook was to increase compliance with the procedures by promoting self-monitoring of pedometer use. At the end of each day, participants were asked to record all of the times when they removed the pedometer during the day – there was no penalty for removing the pedometer – and to note what they were doing while not wearing the pedometer (e.g., sleeping). Note that participants did not need to record the number of steps taken each day (this value was stored on the pedometer and downloaded at the end of the assessment period) so the self-monitoring was specific to procedural compliance and should have had a negligible effect on physical activity. These logbooks were collected at the end of each week to record non-wear times for each pedometer.

Procedures

On the second Thursday of the semester, participants attended individual assessment appointments and the procedures for the study were described. Participants rated their physical activity intentions for the upcoming week on a password-protected website during that baseline session (study week 0). Participants were instructed to logon to this website between noon and midnight every subsequent Thursday and rate their physical activity intentions for the week ahead. These ratings were made weekly for 9 additional weeks, with a one-week hiatus after study week 6 to correspond with the university's spring break when participants were not guaranteed to have internet access (and presumably had different contextual constraints than the other weeks). In the initial laboratory assessment session, a research assistant measured participants' height and weight twice; if values differed by more than 0.4 cm or 0.3 kg, a third measurement was taken and the average value was used to calculate BMI. The research assistant then gave participants a pedometer to wear each day for the next four weeks, and provided training on (a) how to wear the pedometer to ensure valid measurement, and (b) how to complete the daily log of pedometer usage. All procedures were approved by an Institutional Review Board.

Data Analysis

All three research questions involved multilevel data structures. For the first and third question, multilevel models were estimated using HLM 6.08 (Scientific Software International, Chicago, IL). HLM tolerates missing data at Level-1 by excluding days with one or more missing data points and estimating intercepts and slopes based on available data; missing data at level-2 or level-3 resulted in listwise deletion. For the second question,

latent growth curve models were estimated using AMOS 18 (Arbuckle, 2009). Full information maximum likelihood estimates were used to handle missing data in the growth curve analyses.

Research question 1—Weekly intentions were nested within people (i.e., a two-level data structure). Physical activity intentions rated during study week 6 represented intentions for the week of spring break and were highly discrepant from all other ratings. Given the contextual change for these ratings, they were excluded to provide a more conservative test of within-person variability hypotheses. Data from the final week, study week 10, were disproportionately missing (24%) and therefore also excluded from the analyses that follow. The resulting eight weeks of intention data yielded a total of 242 intention ratings (92% of the possible ratings). Complete data was obtained from 52% of the participants, and 36% missed only a single occasion. A total of four participants missed either two or three occasions (6% each). A variance components analysis was conducted to estimate intraclass correlation coefficients which reflected the proportion of between-person variance in physical activity intentions.

Research question 2—A series of nested growth curve models were estimated and compared to evaluate the form that best characterized within-person trajectories for behavioral intentions. In these models, intercepts represented behavioral intentions at the first assessment (manifest intercepts were constrained to zero to move mean information to the intercept), and slopes represented the rates at which those intentions changed each week. Our a priori model, which served as the baseline for model comparisons, included a randomly-varying intercept, randomly-varying linear slope, and a randomly-varying quadratic slope. Covariances between the growth factors were causing estimation problems in some models so they were constrained to zero under the assumption that they were negligible. The following parameters were individually constrained to zero in the progression of nested model comparisons: quadratic slope variance (Model 2), quadratic slope mean (Model 3), linear slope variance (Model 4), linear slope mean (Model 5), and intercept variance (Model 6). When a constraint was found to reduce model fit significantly, it was released in all subsequent models (i.e., only constraints that did not significantly reduce model fit were retained in subsequent models).

Debate over the best cut-off criteria for evaluating model fit has long been a controversial topic which continues to evolve (Marsh, Hau, & Wen, 2004). In light of this state of affairs, we emphasized fit comparisons between nested competing models to determine the best, theoretically-plausible model. We then evaluated its fit relative to conventional criteria to elaborate our interpretation (recognizing the limitations inherent in using cutoff criteria). In addition to the model χ^2 statistic, we reported the comparative fit index (CFI), Tucker-Lewis index (TLI), and the root mean square error of approximation (RMSEA). CFI and TLI, also known as the non-normed fit index, are incremental fit indices which generally range from 0 to 1.0; higher values indicate better fit. RMSEA is an absolute measure of standardized model misfit; smaller values indicate better fit. According to conventional criteria, acceptable model fit is indicated by CFI > .90, TLI > .90, and RMSEA < .08; excellent model fit is indicated by CFI > .95, TLI > .95, and RMSEA < .06 (Hu & Bentler, 1998,

1999; Marsh et al., 2004). In evaluating growth curve models, these fit indices inform us of misfit in covariance structures and marginal means, and RMSEA is particularly sensitive to misspecification of the functional form of change (Wu, West, & Taylor, 2009).

Research question 3—Daily step counts were nested within weeks which were nested within people so we estimated a three-level model. The level-1 data file had 787 data points representing daily step counts (88% possible), the level-2 data file had 120 data points representing weeks of data (91% possible), and the level-3 data file had 31 data points representing participants (94% possible). Three data transformations were implemented to prepare for the multilevel analysis of intention-behavior coupling. First, between-person differences in overall activity levels which can obscure the within-person processes of interest (Allison, 2005) so we person-centered each daily step count. This daily deviation from intraindividual mean steps score (hereafter simply labeled step counts) was used as the dependent variable in subsequent analyses and represented the degree to which a person was more- or less-active-than-usual on a given day. This approach parallels fixed effects modeling (Allison, 2005) which reduces contamination from both measured and unmeasured between-person correlates of intentions and physical activity (e.g., efficacy beliefs). Although this approach effectively eliminates the possibility of between-person main effects, between-person variables may still moderate associations between outcomes and within-person predictors so they are included in the model. Next, the intention ratings preceding each week of physical activity assessment were decomposed into between- and within-person components (Bolger, Davis, & Rafaeli, 2003). Between-person differences in *overall intention strength* were estimated by the mean of each participant's four intention ratings. When interpreting this variable, people with higher scores were viewed as "strong intenders" and those with lower scores were viewed as "weak intenders." Within-person *weekly intention deviations* were estimated as the difference between a given weekly intention rating and that person's overall intention strength across the four weeks (i.e., person-centered scores). The overall intention strength and weekly intention deviation scores were used as Level-2 (week) and Level-3 (person) predictors, respectively, when predicting daily step counts. Between-person differences in *intention stability* across the four weeks of physical activity assessment were estimated by aggregating standardized scores representing (1) the sum of absolute differences in corresponding items, (2) the mean proportion of possible change in items based on the initial response (i.e., adjusted difference score), (3) the number of items with different responses over time, and (4) the within-person correlation of item responses at two time points (Conner et al., 2000). Finally, a dummy variable was calculated to represent whether the daily step count was assessed on a weekday (0) or weekend (1). This variable was entered as a level-1 (day) predictor variable to account for weekday-weekend differences in step counts. The model describing change in step counts on day d during week w for individual i was represented by the following equations:

Level-1 (Day-Level) Model Equations:

$$\text{Step Counts}_{dwi} = \beta_{0wi} + \beta_{1wi}(\text{Weekend}_{dwi}) + r_{dwi} \quad (1)$$

Level-2 (Week-Level) Model Equations:

$$\beta_{0wi} + \beta_{00i} + \beta_{01i}(\text{Intention Deviation}_{wi}) + u_{0wi} \quad (2)$$

$$\beta_{1wi} + \beta_{10i} + \beta_{11i}(\text{Intention Deviation}_{wi}) + u_{1wi} \quad (3)$$

Level-3 (Person-Level) Model Equations:

$$\begin{aligned} \beta_{00i} = & \gamma_{000} + \gamma_{001}(\text{Overall Intention Strength}_i) \\ & + \gamma_{002} + (\text{Stability}_i) \\ & + \gamma_{003}(\text{Overall Intention Strength}_i \times \text{Stability}_i) + e_{00i} \end{aligned} \quad (4)$$

$$\beta_{01i} + \gamma_{010} + \gamma_{011}(\text{Overall Intention Strength}_i) + e_{01i} \quad (5)$$

$$\begin{aligned} \beta_{10i} + \gamma_{100} + \gamma_{101}(\text{Overall Intention Strength}_i) \\ & + \gamma_{102}(\text{Stability}_i) \\ & + \gamma_{103}(\text{Overall Intention Strength}_i \times \text{Stability}_i) + e_{10i} \end{aligned} \quad (6)$$

$$\beta_{11i} + \gamma_{110} + \gamma_{111}(\text{Overall Intention Strength}_i) + e_{11i} \quad (7)$$

The level-1 (daily) model, shown in Equation 1, decomposed peoples' daily step counts into an average weekday deviation from their average step count (β_{0wi}) and the difference in their average weekend-weekday deviation (β_{1wi}). The level-2 (weekly) model, shown in Equations 2–3, decomposed the daily intercept (β_{0wi}) and slope (β_{1wi}) parameters into weekly intercepts (β_{00i} , β_{10i}) and the effects of weekly within-person deviations in intentions (β_{01i} , β_{11i}). The level-3 (person) model, shown in Equations 4–7, regressed (a) weekly intercepts (γ_{000} , γ_{100}) on between-person differences in overall intention strength (γ_{001} , γ_{101}) and intention stability (γ_{002} , γ_{102}), and (b) slopes for weekly deviations in intentions (β_{01i} , β_{11i}) on between-person differences in overall intention strength (γ_{011} , γ_{111}) alone. Intention stability was excluded from the level-3 model predicting level-2 slopes because stability is a dynamic characteristic of the entire time period and its effects should not vary by week.

Results

Descriptive statistics for behavioral intentions and weekly step counts are presented in Table 1. Physical activity intention means decreased and standard deviations increased over the study period. The observed step counts were low relative to established values for healthy adults and college students but consistent with a “somewhat active” lifestyle (Behrens & Dinger, 2005; Tudor-Locke & Bassett, 2004; Tudor-Locke & Myers, 2001).

Research Question 1: Decomposing Within-Person Variability in Behavioral Intentions

The first variance components analysis was conducted using eight behavioral intention assessments over the 10-week period. The resulting intraclass correlation coefficient

indicated that 54% of the variance in weekly behavioral intentions existed between-people. The thin lines in Figure 1 represent within-person trajectories for intentions and clearly illustrate the mixture of within-person variability in these intentions over time. When this analysis was repeated with data from the four weeks lagged ahead of the physical activity assessment, the intraclass correlation was similar (.59).

Research Question 2: Evaluating Time-Structured Change Models

Table 2 presents the fit indices for the linear, time-structured growth models. The only constraint on the baseline model (quadratic growth) which did not significantly decrease fit was the constraint on the quadratic slope variance ($p > .05$). All other constraints significantly reduced model fit, as indicated by chi-square difference tests ($p < .05$), and were rejected accordingly. Therefore, initial intentions varied significantly between people, and changed in the weeks that followed. People varied in their rates of linear change, but not in their rate of quadratic change. The final growth parameters from this model were as follows: intercept mean = 6.43 (SE = 0.15, $p < .001$), intercept variance = 0.56 (SE = 0.16, $p < .001$), linear slope mean = -0.14 (SE = .05, $p = .004$), linear slope variance = 0.01 (SE = 0.003, $p = .006$), and quadratic slope mean = 0.01 (SE = 0.005, $p = .031$). The estimated mean trajectory for intentions is depicted by the heavy line in Figure 1. Although this model of time-structured change fit best among the models tested, it was clear from the fit indices in Table 2 and the trajectories in Figure 1 that this model did not adequately represent the within-person variability in participants' intentions to exercise. Based on the finding that this linear, time-structured growth model failed to fit the data adequately, we concluded that this type of model was unlikely to be sufficient for describing within-person variability in intentions.

Research Question 3: Coupling Within-Person Variability in Behavioral Intentions with Physical Activity

A variance components analysis of daily step counts indicated that 27% of the variance in daily step counts existed between-people, with the remaining 73% existing within-people. Figure 2 presents within-person trajectories for uncentered (top panel) and centered (bottom panel) daily step counts. The weekly cycle of activity can be seen in this plot with the nadirs in trajectories tending to occur on weekends.

Table 3 presents the final coefficients from the multilevel model with daily step counts as the outcome. As expected, intention stability did not significantly predict step counts on either weekends or weekdays, either as a direct effect (γ_{002} , γ_{102}) or in interaction with overall intention levels (γ_{003} , γ_{103}). In contrast, as a product of a dynamic process, weekly intention deviations significantly predicted context-specific step counts as indicated by the statistically significant 3-way interaction between overall intentions, weekly intention deviations, and weekends (γ_{111}).

Figure 3 presents this interaction and clearly illustrates the difference in step counts between weekdays (top two lines) and weekends (bottom two lines). To interpret this interaction, simple slopes (ω) were calculated by transferring HLM coefficients along with their asymptotic variances and covariances to an online utility that interfaces with an Rweb server

(Preacher, Curran, & Bauer, 2006). This analysis revealed that the association between daily step counts and weekday/weekend-status varied as a function of both between- and within-person intentions. For people with strong overall intentions, step counts were greater on weekdays than weekends when people had stronger-than-usual intentions ($\omega = -3700.4$, $z = -5.70$, $p < .001$). There was no weekend-weekday difference in step counts when strong intenders had weaker-than-usual intentions ($\omega = -1627.0$, $z = -1.75$, ns). For people with weak overall intentions, step counts were greater on weekdays than weekends regardless of whether people had stronger-than-usual ($\omega = -3623.7$, $z = -5.74$, $p < .001$) or weaker-than-usual ($\omega = -5156.1$, $z = -7.00$, $p < .001$) intentions.

In sum, for strong intenders, intentions and behavior were coupled selectively based on the daily context. This selective coupling ensured a consistent level of activity for the week. When strong intenders' intentions were stronger-than-usual and weekday physical activity was greater-than-usual, people's weekend physical activity was lower-than-usual. In contrast, for weak intenders, intentions were decoupled from subsequent physical activity regardless of daily context.

Discussion

In this study, we evaluated a within-person approach to studying physical activity intentions as a means of understanding the intention-behavior gap. As expected, results indicated that (1) approximately half of the variability in physical activity intentions existed within-people, (2) linear models of time-structured change processes were unlikely to be sufficient for fully characterizing that variability, and (3) intention-behavior relations were regulated by the product of a dynamic process which selectively coupled motivation and action.

Only half of the variability in intentions could be attributed to between-person differences, both in this study as well as others which have sampled physical activity intentions on biweekly and monthly timescales (Scholz et al., 2009; Scholz et al., 2008). Although consistent with research on physical activity intentions, this proportion contrasts with estimates associated with other health behaviors (e.g., daily condom use intentions exhibit considerably less within-person variation; Kiene, Tennen, & Armeli, 2008). The substantial within-person variability in physical activity intentions casts a new light on existing research which has largely focused on between-person differences in those intentions. The contributions of cross-sectional studies in establishing basic associations between intentions and physical activity is incontrovertible (Downs & Hausenblas, 2005; Hagger et al., 2002), but it is apparent that these studies tell only half of the story. After dipping our toes in the within-person "motivational stream" and seeing how variable physical activity intentions are, we conclude that our theories and methods need to be sensitive to both between-person and within-person sources of variability.

This process of theoretical and methodological enhancement is underway with research that examines the stability of physical activity intentions. In one branch of that work, however, stability has generally been treated as a dynamic characteristic (i.e., a between-person difference), which requires some restrictive assumptions about the nature of the changes that people experience in their intentions. It may therefore be insensitive to certain forms of

change, especially if the researchers inadvertently select the wrong sampling frequency. For example, this approach is only sensitive to the magnitude and not the direction of changes in intention strength. Our results indicate that it very much matters whether intentions are stronger- or weaker-than-usual when predicting behavior.

This study extends conclusions that the rate of within-person change in intentions both indirectly and directly predicts changes in activity (Reuter et al., 2009; Scholz et al., 2009). We found that changes in intentions over 10 weeks were partly time-structured but that the models we tested were insufficient for capturing this variability adequately. Whether the observed intention variation was produced by cognitive changes, reactivity to study procedures, self-monitoring or another process is unclear from these data. An important task for future research will involve determining the source(s) of variability in behavioral intentions. It is plausible that such variability might derive, in part, from stability maintenance processes on faster timescales (e.g., the need to balance activity and rest on a daily basis) and transformational change processes on slower timescales (e.g., seasonal revisions of physical activity goals) (see Ram & Gerstorf, 2009).

In the present study, within-person variability in intentions was coupled with physical activity for strong intenders on weekdays, but not on weekends or for weak intenders. Although few studies explicitly address contextual changes, such as the day of week, as an influence on within-person variability in physical activity, our findings reinforce the perspective that people's behavior is better understood as a function of the person in context than in a decontextualized vacuum (e.g., Shoda, Cervone, & Downey, 2007). The weekend decoupling was especially intriguing given the dramatic decrease observed in participants' physical activity over the weekends. We speculate that self-regulatory depletion at the end of the week accounts for this breakdown (Martin Ginis & Bray, 2010; Muraven & Baumeister, 2000) – people may simply prioritize the restoration of self-regulatory resources over actual self-control on the weekends, resulting in an intention-behavior gap. This effect occurs despite the increase in college students' discretionary leisure time over the weekend, and is not an artifact of decaying intention strength because intentions were assessed on Thursday afternoons and evenings, shortly before each weekend began.

There are other plausible reasons for their weekend decoupling as well, including the possibility that college students simply have different time use priorities on weekends relative to weekdays. For example, people spend more time socializing and communicating on weekends than on weekdays (U.S. Bureau of Labor Statistics, 2010). College students also consume more alcohol more on weekends than on weekdays, sleep longer on weekends to make up for weekday sleep deficits, and select more sedentary leisure pursuits on weekends than weekdays (Del Boca, Darkes, Greenbaum, & Goldman, 2004; Gaultney, 2010; Lake, Townshend, Alvanides, Stamps, & Adamson, 2009). Alternatively, it is also possible that weekday physical activity intentions were simply more salient when participants rated intentions for the week ahead.

People with weaker overall intentions failed to exhibit the expected intention-behavior coupling in either daily context. The decontextualization of this process is significant. Emotion researchers consider decontextualization of emotions to be an indicator of

maladjustment (Kuppens, Allen, & Sheeber, in press). Our findings indicate that decontextualization of motivation is also dysfunctional and that weak intenders are at risk for this self-regulatory vulnerability. Cross-sectional studies consistently report that weak intenders tend to be less active than strong intenders (Downs & Hausenblas, 2005; Hagger et al., 2002), and this evidence has led to intention formation becoming a popular physical activity intervention (Michie, Abraham, Whittington, McAteer, & Gupta, 2009). Our findings extended that work by demonstrating the importance of sustaining strengthened intentions so that they can begin to couple with subsequent physical activity. Sporadically strengthened intentions were insufficient for increasing physical activity, even when the intentions are relatively strong at times. This finding converged with research conceiving of intention stability as a dynamic characteristic and showing that physical activity was greatest for people with stable strong intentions (Li & Chan, 2008; Rhodes et al., 2010; Sheeran & Abraham, 2003). It also extended that work by demonstrating very clearly that this coupling extends to objectively-measured physical activity over an extended surveillance period, and at a faster timescale than previously observed. This study also disentangled the effects of between- and within-person variation in both intentions and physical activity. Thus, these findings contribute to the science of *individual* physical activity motivation and behavior.

From a practical standpoint, these results highlight the importance of attending to temporal fluctuations in motivation when promoting physical activity. People's motivation varies over time and the best intentions do not always translate into behavior. For these reasons, practitioners who endeavor to promote physical activity would benefit from developing a multifaceted approach with their clients – what works under the constraints of weekday life may not work once those constraints change on the weekend. Our findings also point to the value in promoting consistently strong intentions over time. Every lapse in intentions will weaken overall intention strength, and overall intention strength was instrumental in coupling intentions with behavior in this study. Practitioners should also keep in mind that self-regulation is only one source of physical activity, and some motivational processes that regulate physical activity lie outside of conscious awareness (Conroy, Hyde, Doerksen, & Ribeiro, 2010).

Some caveats and limitations of this study warrant attention. First, intentions were reported on a weekly schedule and it is presently unclear whether our conclusions will generalize to other timescales. Second, this sample was drawn from a very specific (and WEIRD – western, educated, industrialized, rich, democratic; Henrich, Heine, & Norenzayan, in press) population so conclusions may not generalize widely. It will be especially important to replicate these results in populations with similar and contrasting contextual constraints on physical activity (e.g., working vs. retired adults). Third, model convergence problems in our growth curve analyses required us to assume that the initial level of intention strength was not associated with the rate at which intentions changed in subsequent weeks. The validity of our conclusions will be impacted by the validity of this assumption so it should be tested in future research. Ideally, this research will be based on larger sample sizes to reduce bias in standard errors for person-level coefficients and possibly eliminate the convergence problem encountered in this study. Next, we focused on step counts which represent only a portion of total physical activity variance. Our approach to processing the

data also may have somewhat under- or over-estimated actual daily step counts. Finally, we sampled motivation and behavior at different timescales and further research based on a common sampling frequency (e.g., daily intentions and daily behavior) would be valuable.

In conclusion, the widely-documented intention-behavior gap has challenged motivation theorists to develop creative extensions and elaborations of basic self-regulatory processes that explain health behaviors. One approach to bridging this gap focuses on the stability of intentions as a moderator of intention-behavior relations. We focused on the stream of intentions and behavior that unfold within people over time. An ecological momentary assessment study illuminated the substantial within-person variability in physical activity intentions, demonstrated that this change was not entirely time-structured, and revealed how the person and context interacted to couple or decouple intentions from physical activity. Diving into the within-person motivational stream afforded us a unique perspective on the conditions that bridge the intention-behavior gap, and we encourage others to test these waters as well.

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References

- Ajzen I. The theory of planned behavior. *Organizational Behavior and Human Decision Processes*. 1991; 50(2):179–211.
- Ajzen, I. The directive influence of attitudes on behavior. In: Gollwitzer, PM.; Bargh, JA., editors. *The psychology of action: Linking cognition and motivation to behavior*. New York: Guilford Press; 1996. p. 385–403.
- Allison, PD. *Fixed effects regression methods for longitudinal data using SAS*. SAS Institute; 2005.
- Arbuckle, JL. *Amos (Version 18)*. Chicago: SPSS; 2009.
- Bassili JN. Response latency versus certainty as indexes of the strength of voting intentions in a CATI survey. *Public Opinion Quarterly*. 1993; 57(1):54–61.
- Behrens TK, Dinger MK. A preliminary investigation of college students' physical activity patterns. *American Journal of Health Studies*. 2003; 18:169–172.
- Behrens TK, Dinger MK. Ambulatory physical activity patterns of college students. *American Journal of Health Education*. 2005; 36:221–227.
- Bolger N, Davis A, Rafaeli E. Diary methods: Capturing life as it is lived. *Annual Review of Psychology*. 2003; 54:579–616.
- Conner M, Sheeran P, Norman P, Armitage CJ. Temporal stability as a moderator of relationships in the Theory of Planned Behaviour. *British Journal of Social Psychology*. 2000; 39(4):469–493. [PubMed: 11190681]
- Conroy DE, Hyde AL, Doerksen SE, Ribeiro NF. Implicit attitudes and explicit motivation prospectively predict physical activity. *Annals of Behavioral Medicine*. 2010; 39:112–118. [PubMed: 20140542]
- Cooke R, Sheeran P. Moderation of cognition-intention and cognition-behaviour relations: A meta-analysis of properties of variables from the theory of planned behaviour. *British Journal of Social Psychology*. 2004; 43:159–186. [PubMed: 15285829]

- Del Boca FK, Darkes J, Greenbaum PE, Goldman MS. Up close and personal: Temporal variability in the drinking of individual college students during their first year. *Journal of Consulting and Clinical Psychology*. 2004; 72:155–164. [PubMed: 15065951]
- Downs DS, Hausenblas HA. The Theories of Reasoned Action and Planned Behavior applied to exercise: A meta-analytic update. *Journal of Physical Activity and Health*. 2005; 2(1):76–97.
- Gaultney JF. The prevalence of sleep disorders in college students: Impact on academic performance. *Journal of American College Health*. 2010; 59:91–97. [PubMed: 20864434]
- Godin G, Sheeran P, Conner M, Bélanger-Gravel A, Gallani MCBJ, Nolin B. Social structure, social cognition, and physical activity: A test of four models. *British Journal of Health Psychology*. 2010; 15(1):79–95. [PubMed: 19321038]
- Hagger MS, Chatzisarantis NLD, Biddle SJH. A meta-analytic review of the theories of reasoned action and planned behavior in physical activity: Predictive validity and the contribution of additional variables. *Journal of Sport & Exercise Psychology*. 2002; 24(1):3–32.
- Hardeman W, Kinmonth AL, Michie S, Sutton S. Theory of planned behavior cognitions do not predict self-reported or objective physical activity levels of change in the *ProActive* trial. *British Journal of Health Psychology*. 2011; 16:135–150. [PubMed: 21226788]
- Henrich J, Heine SJ, Norenzayan A. The weirdest people in the world? *Behavioral and Brain Sciences*. (in press).
- Hu LT, Bentler PM. Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods*. 1998; 3:424–453.
- Hu LT, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*. 1999; 6:1–55.
- Kiene SM, Tennen H, Armeli S. Today I'll use a condom, but who knows about tomorrow: A daily process study of variability in predictors of condom use. *Health Psychology*. 2008; 27(4):463–472. [PubMed: 18643004]
- Krosnick, JA.; Petty, RE. Attitude strength: An overview. In: Petty, RE.; Krosnick, JA., editors. *Attitude strength: Antecedents and consequences*. Hillsdale, NJ, England: Lawrence Erlbaum Associates; 1995. p. 1-24.
- Kuppens P, Allen NB, Sheeber LB. Emotional inertia and psychological maladjustment. *Psychological Science*. (in press).
- Lake AA, Townshend T, Alvanides S, Stamps E, Adamson AJ. Diet, physical activity, sedentary behaviour and perceptions of the environment in young adults. *Journal of Human Nutrition and Dietetics*. 2009; 22:444–454. [PubMed: 19743982]
- Li K-K, Chan DKS. Goal conflict and the moderating effects of intention stability in intention-behavior relations: Physical activity among Hong Kong Chinese. *Journal of Sport & Exercise Psychology*. 2008; 30(1):39–55. [PubMed: 18369242]
- Marsh HW, Hau K-T, Wen Z. In search of golden rules: Comment on hypothesis-testing approaches to setting cutoff values for fit indexes and dangers in overgeneralizing Hu and Bentler's (1999) findings. *Structural Equation Modeling*. 2004; 11:320–341.
- Martin Ginis KA, Bray SR. Application of the limited strength model of self-regulation to understanding exercise effort, planning and adherence. *Psychology and Health*. 2010; 25:1147–1160. [PubMed: 20204951]
- Michie S, Abraham C, Whittington C, McAteer J, Gupta S. Effective techniques in healthy eating and physical activity interventions: A meta-regression. *Health Psychology*. 2009; 28(6):690–701. [PubMed: 19916637]
- Montaño, DE.; Kasprzyk, D. Theory of reasoned action, theory of planned behavior, and the integrated behavioral model. In: Glanz, K.; Rimer, BK.; Viswanath, K., editors. *Health behavior and health education: Theory, research, and practice*. 4th ed. San Francisco: Jossey-Bass; 2008. p. 67-96.
- Muraven M, Baumeister RF. Self-regulation and depletion of limited resources: Does self-control resemble a muscle? *Psychological Bulletin*. 2000; 126(2):247–259. [PubMed: 10748642]
- Norman P, Smith L. The theory of planned behaviour and exercise: An investigation into the role of prior behaviour, behavioural intentions and attitude variability. *European Journal of Social Psychology*. 1995; 12(4):403–415.

- Orbell S, Sheeran P. "Inclined abstainers": A problem for predicting health-related behaviour. *British Journal of Social Psychology*. 1998; 37(2):151–165. [PubMed: 9639861]
- Ouellette JA, Wood W. Habit and intention in everyday life: The multiple processes by which past behavior predicts future behavior. *Psychological Bulletin*. 1998; 124(1):54–74.
- Physical Activity Guidelines Advisory Committee. Physical Activity Guidelines Advisory Committee Report. Washington, DC: U. S. Department of Health and Human Services; 2008.
- Preacher KJ, Curran PJ, Bauer DJ. Computational tools for probing interactions in multiple linear regression, multilevel modeling, and latent curve analysis. *Journal of Educational and Behavioral Statistics*. 2006; 31:437–448.
- Ram N, Gerstorf D. Time-structured and net intraindividual variability: Tools for examining the development of dynamic characteristics and processes. *Psychology and Aging*. 2009; 24(4):778–791. [PubMed: 20025395]
- Reuter T, Ziegelmann JP, Lippke S, Schwarzer R. Long-term relations between intentions, planning, and exercise: A 3-year longitudinal study after orthopedic rehabilitation. *Rehabilitation Psychology*. 2009; 54(4):363–371. [PubMed: 19929117]
- Rhodes R, de Bruijn G-J, Matheson DH. Habit in the physical activity domain: Integration with intention temporal stability and action control. *Journal of Sport & Exercise Psychology*. 2010; 32(1):84–98. [PubMed: 20167953]
- Rhodes RE, Blanchard CM, Matheson DH. A multicomponent model of the theory of planned behaviour. *British Journal of Health Psychology*. 2006a; 11(1):119–137. [PubMed: 16480559]
- Rhodes RE, Blanchard CM, Matheson DH, Coble J. Disentangling motivation, intention, and planning in the physical activity domain. *Psychology of Sport and Exercise*. 2006b; 7(1):15–27.
- Scholz U, Keller R, Perren S. Predicting behavioral intentions and physical exercise: A test of the health action process approach at the intrapersonal level. *Health Psychology*. 2009; 28(6):702–708. [PubMed: 19916638]
- Scholz U, Nagy G, Schüz B, Ziegelmann JP. The role of motivational and volitional factors for self-regulated running training: Associations on the between- and within-person level. *British Journal of Social Psychology*. 2008; 47(3):421–439. [PubMed: 18096109]
- Schwarzer R. Modeling health behavior change: How to predict and modify the adoption and maintenance of health behaviors. *Applied Psychology: An International Review*. 2008; 57:1–29.
- Sheeran, P. Intention-behaviour relations: A conceptual and empirical review. In: Stroebe, W.; Hewstone, M., editors. *European review of social psychology*. Vol. 12. London: Wiley; 2002. p. 1–36.
- Sheeran P, Abraham C. Mediator of moderators: Temporal stability of intention and the intention-behavior relation. *Personality and Social Psychology Bulletin*. 2003; 29(2):205–215. [PubMed: 15272948]
- Sheeran P, Orbell S. Implementation intentions and repeated behaviour: Augmenting the predictive validity of the theory of planned behaviour. *European Journal of Social Psychology*. 1999; 29(2–3):349–369.
- Shoda, Y.; Cervone, D.; Downey, G., editors. *Persons in context: Building a science of the individual*. New York: Guilford Press; 2007.
- Sisson SB, McClain JJ, Tudor-Locke C. Campus walkability, pedometer-determined steps, and moderate-to-vigorous physical activity: A comparison of 2 university campuses. *Journal of American College Health*. 2008; 56(5):585–592. [PubMed: 18400673]
- Stone, AA.; Shiffman, S.; Atienza, AA.; Nebeling, L. Historical roots and rationale of ecological momentary assessment (EMA). In: Stone, AA.; Shiffman, S.; Atienza, AA.; Nebeling, L., editors. *The science of real-time data capture*. New York: Oxford University Press; 2007.
- Telama R, Yang X, Viikari J, Välimäki I, Wanne O, Raitakari O. Physical activity tracking from childhood to adulthood: A 21-year tracking study. *American Journal of Preventive Medicine*. 2005; 28:267–273. [PubMed: 15766614]
- Tudor-Locke C, Bassett DR. How many steps/day are enough? Preliminary pedometer indices for public health. *Sports Medicine*. 2004; 34:1–8. [PubMed: 14715035]

- Tudor-Locke C, Myers AM. Methodological considerations for researchers and practitioners using pedometers to measure physical (ambulatory) activity. *Research Quarterly for Exercise and Sport*. 2001; 72:1–12. [PubMed: 11253314]
- U.S. Bureau of Labor Statistics. Table A-2. Time spent in detailed primary activities and percent of the civilian population engaging in each detailed primary activity category, averages per day by sex on weekdays and weekends, 2009 annual averages. American Time Use Survey – 2009 results [Press release]. 2010. Retrieved May 18, 2010, from <http://www.bls.gov/news.release/atus.nr0.htm>
- Wu W, West SG, Taylor AB. Evaluating model fit for growth curve models: Integration of fit indices from SEM and MLM frameworks. *Psychological Methods*. 2009; 14:183–201. [PubMed: 19719357]

Figure 1.

Observed within-person (light lines) and estimated mean (heavy line) trajectories for behavioral intentions each week. Week 6 immediately preceded spring break (no data were collected during the week of spring break).

Figure 2.
Within-person trajectories for daily step counts (top panel) and person-centered daily step counts in weeks 0–3.

Figure 3.

Interaction between day-of-week (level-1), weekly intention residuals (level-2) and weekly intention means (level-3) predicting daily step counts.

Table 1

Descriptive statistics for weekly intentions and average daily step counts

	<u>Intentions for Week Ahead</u>		<u>Average Daily Step Counts</u>	
	<u>M</u>	<u>SD</u>	<u>α</u>	
Week 0	6.47	0.76	.91	7815.2
Week 1	6.00	1.20	.97	7702.3
Week 2	6.08	1.05	.96	7540.4
Week 3	6.17	1.17	.98	7707.3
Week 4	6.05	1.41	.95	—
Week 5	6.00	1.44	.98	—
Week 8	6.10	1.22	.95	—
Week 9	6.00	1.28	.98	—

Table 2

Fit indices and model comparisons for growth curve models of physical activity intentions

Model	New Constraint	χ^2	df	CFI	TLI	RMSEA (90% CI)
1	None – baseline model	49.52	30	.87	.84	.14 (.07, .21)
2	Baseline model + Quadratic slope variance = 0	50.51	31	.87	.85	.14 (.06, .21)
3	Model 2 + Quadratic slope mean = 0	54.73	32	.85	.83	.15 (.08, .22)
4	Model 2 + Linear slope variance = 0	61.61	32	.80	.78	.17 (.11, .23)
5	Model 2 + Linear slope mean = 0	57.49	32	.83	.81	.16 (.09, .22)
6	Model 2 + Intercept variance = 0	116.49	32	.44	.37	.29 (.23, .34)

Note. CFI = Comparative Fit Index, TLI = Tucker-Lewis Index, RMSEA = Root Mean Square Error of Approximation, CI = confidence interval.

Table 3

Multilevel model coefficients predicting within-person fluctuations in physical activity

	Coefficient	Standard Error
Intercept	**968.5	118.0
Overall intention strength	-306.4 [†]	176.7
Intention stability	201.9	155.6
Overall intention strength X Intention stability	-56.1	84.1
Weekly deviations in intentions	17.2	242.3
Weekly deviations in intentions X Overall intention strength	501.0 [†]	285.9
Weekend	-3399.5**	389.1
Weekend X Overall intention strength	969.8 [†]	561.9
Weekend X Intention stability	-515.5	422.8
Weekend X Overall intention strength X Intention stability	222.8	280.8
Weekend X Weekly deviations in intentions	-126.4	355.0
Weekend X Weekly deviations in intentions X Overall intention strength	-946.6*	412.5

Note. Robust standard errors are reported to relieve assumptions about homogeneity of random effects.

**
 $p < .01$,

*
 $p < .05$

[†]
 $p < .10$.