Within-Day Time-Varying Associations Between Behavioral Cognitions and Physical Activity in Adults

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Abstract:

This study used time-varying effect modeling to examine time-of-day differences in how behavioral cognitions predict subsequent physical activity (PA). Adults (N = 116) participated in three 4-day “bursts” of ecological momentary assessment (EMA). Participants were prompted with eight EMA questionnaires per day assessing behavioral cognitions (i.e., intentions, self-efficacy, outcome expectations) and wore an accelerometer during waking hours. Subsequent PA was operationalized as accelerometer-derived minutes of moderate- or vigorous intensity PA in the 2 hr following the EMA prompt. On weekdays, intentions positively predicted subsequent PA in the morning (9:25 a.m.–11:45 a.m.) and in the evening (8:15 p.m.–10:00 p.m.). Self-efficacy positively predicted subsequent PA on weekday evenings (7:35 p.m.–10:00 p.m.). Outcome expectations were unrelated to subsequent PA on weekdays. On weekend days, behavior cognitions and subsequent PA were unrelated regardless of time of day. This study identifies windows of opportunity and vulnerability for motivation-based PA interventions aiming to deliver intervention content within the context of adults’ daily lives.

Keywords: exercise | motivation | ecological momentary assessment | time-varying effect models

Article:

Despite the wide array of benefits associated with engaging in regular physical activity (Physical Activity Guidelines Advisory Committee, 2008), approximately 30% of individuals globally are insufficiently active and among developed nations this percentage is even higher (Hallal et al., 2012). Enhancing motivation for physical activity is viewed as a promising way to increase physical activity among individuals who are insufficiently active. Evidence supporting motivational theories regarding physical activity has largely focused on explaining relations between a person's typical motivation and his or her typical behavior (i.e., between-persons processes; Rhodes & Nigg, 2011; Sniehotta, Presseau, & Araújo-Soares, 2014); however, there is limited evidence documenting how motivation changes within the context of daily life and how those changes influence subsequent physical activity (i.e., within-person processes). This study examines time-varying associations between physical activity and behavioral cognitions over the course of the day.

BEHAVIORAL COGNITIONS AND PHYSICAL ACTIVITY

Social cognitive theory emphasizes a triadic, reciprocal relationship between a person's cognitions, behavior, and environment (Bandura, 1998). Behavioral cognitions, such as goals (i.e., intentions), beliefs about one's abilities (i.e., self-efficacy), or expected benefits of a behavior (i.e., outcome expectations), therefore, have the potential to change behavior and represent viable targets for interventions designed to increase physical activity. The majority of work documenting associations between behavioral cognitions and physical activity focuses on between-persons differences (e.g., explaining relations between a person's typical motivation and his or her typical behavior). This approach may be partially flawed because the association between a person's typical motivation and typical behavior over time may not resemble the association between that person's momentary levels of behavioral cognitions and momentary behavior at a given point in time (Molenaar, Huizenga, & Nesselroade, 2003). To the extent that motivational processes change over time, the ability of those processes to regulate behavior also may change (Conroy, Elavsky, Doerksen, & Maher, 2013; Conroy, Elavsky, Hyde, & Doerksen, 2011; Pickering et al., 2016). Only by treating time as a meaningful dimension of motivation and behavior can we understand these dynamic processes and subsequently use timing to improve interventions to enhance motivation and, ultimately, change behavior.

WITHIN-PERSON VARIATION IN ASSOCIATIONS BETWEEN PHYSICAL ACTIVITY AND BEHAVIORAL COGNITIONS

Ecological momentary assessment (EMA) and daily diary studies have found that both physical activity and behavioral cognitions vary within people over time at both the momentary and daily level (Conroy, Elavsky, et al., 2013; Conroy et al., 2011; Pickering et al., 2016). These studies have also documented significant linear associations between both momentary and daily behavioral cognitions and subsequent physical activity (Conroy, Elavsky, et al., 2013; Conroy et al., 2011; Pickering et al., 2016). For example, Pickering et al. found that on occasions when intentions and self- efficacy were higher than usual, subsequent physical activity also tended to be higher over the next 2 hr (i.e., a within-person process) even after controlling for usual levels of intentions and self-efficacy (i.e., a between-person process) but that momentary and usual outcome expectations were unrelated to physical activity (Pickering et al., 2016). A limitation of this analysis and others investigating within-person processes is that they have focused exclusively on linear associations between physical activity and behavioral cognition—aggregating associations across the day or across days, respectively, to generate a mean level of association over time.

Behavioral cognitions regarding physical activity, as well as associations between behavioral cognitions and subsequent physical activity, likely change throughout the day. The self-regulation of behavior, via motivational processes such as behavioral cognitions, occurs on an ongoing basis and likely varies with regular depletion and replenishment of self-control resources (e.g., Scholz, Nagy, Schüz, & Ziegelmann, 2008; Shmueli & Prochaska, 2012). As individuals progress throughout the day, they are faced with a variety of decisions, stressors, and even temptations that deplete those resources, subsequently weakening one's ability to self-regulate (Muraven & Baumeister, 2000; Muraven, Tice, & Baumeister, 1998). Therefore, it may be that behavioral cognitions regarding physical activity are higher and subsequently better able to predict physical activity behavior earlier in the day when those regulatory resources are high compared with the afternoon and evening. Moreover, adults may face a variety of contextual factors on weekdays (e.g., a walk from a parking structure to an office building at beginning and end of the workday, work-related meetings, travel to and from job sites, assignment to a particular work location such as a cash register or service counter, appointments) and weekend days (e.g., errands, child care) that influence behavioral cognitions as well as associations between behavioral cognitions and subsequent physical activity throughout the day.

Using nonlinear statistical methods such as time- varying effect models (TVEM) could enhance our understanding of the relations between physical activity and behavior cognitions. Specifically, by applying this advanced statistical method to intensive longitudinal data, one could determine whether the magnitude and direction of the physical activity–behavioral cognition relationship changes as a function of time of day, day of the week, or both. Identifying when behavioral cognitions are more strongly linked with physical activity or when behavioral cognitions adversely impact physical activity is crucial for developing motivation-based physical activity interventions that are designed to be delivered within the context of people's daily lives.

PRESENT STUDY

TVEM investigated the time-varying associations between momentary behavioral cognitions and subsequent change in physical activity on both weekdays and weekend days using data collected through an EMA study employing both intensive within-day assessments and ambulatory physical activity monitoring methods. We hypothesized that associations between behavioral cognitions and subsequent change in physical activity would be more strongly linked in the morning, when regulatory resources are high, compared with the afternoon and evening. Furthermore, we hypothesized that there would be differences in these time-varying associations between a typical weekday and weekend day. In testing these hypotheses, we controlled for potential confounds previously found to be associated with behavioral cognitions and/or physical activity in adults including age, sex, and body mass index (BMI; Caspersen, Pereira, & Curran, 2000; Troiano et al., 2008; Tudor-Locke, Brashear, Johnson, & Katzmarzyk, 2010).

METHODS

Participants

This study analyzed data from Project MOBILE (Measuring Our Behaviors in Living Environments), a longitudinal study that aimed to investigate intrapersonal, interpersonal, and environmental influences on physical activity and eating behaviors (Dunton, Liao, Kawabata, & Intille, 2012). Project MOBILE participants were recruited from Chino, California, and the surrounding area. Inclusion criteria were the following: (a) age 25 years or older (to avoid sampling full-time students) and (b) ability to access a smartphone while at work to complete EMA questionnaires. Potential participants were excluded if they (a) did not speak and read English fluently, (b) had an annual household income greater than U.S. $210,000, (c) regularly performed more than 150 min per week of physical activity, or (d) had a physical limitation that prevented them from exercising. Eligible participants were scheduled for an introductory session.

Ultimately, the sample consisted of 116 community- dwelling adults (M_{age} = 40.3 years, *SD* = 9.6). The majority of the sample identified as female (74.2%). More than two thirds of the sample reported that they were employed (69.7% employed, 16.5% homemaker, 7.3% unemployed, 3.6% retired, <2% other). Participants were split between three BMI categories (38.2% underweight or normal weight, 30.9% overweight, 30.9% obese). A full description of participant characteristics can be found elsewhere (Dunton, Liao, et al., 2012).

Procedures

Figure 1 provides a schematic of the Project MOBILE study design. Participants were asked to complete three separate 4-day “measurement bursts” during which participants were prompted with up to eight EMA surveys per day at random times. Each measurement burst was separated by 6 months.

Before the start of each measurement burst, participants attended an introductory session where they were familiarized with the study procedures, provided con- sent, completed a questionnaire regarding demographic information, and were measured for anthropometric data by a research assistant. In addition, participants were provided with and trained on how to use a mobile phone (HTC Shadow, T-Mobile U.S.A., Bellevue, WA) with a custom version of MyExperience software installed (Froehlich, Chen, Consolvo, Harrison, & Landay, 2007), which supported EMA data collection. Each burst of data collection lasted 4 days (Saturday–Tuesday). Participants received eight EMA prompts over the course of each day. EMA questionnaires were prompted at a random time within eight preprogrammed windows between 6:30 a.m. and 10:00 p.m. When prompted, participants were instructed to stop their current activity and complete a short electronic EMA question sequence (which at any given prompt could include up to 19 items). This process required 2–3 min. Participants were instructed to ignore the prompt if prompted during an incompatible activity (e.g., sleeping, showering, driving). If an EMA questionnaire was not completed after the initial prompt, the phone emitted up to three reminder signals at 5-min intervals. Following the third reminder, the EMA questionnaire became inaccessible until the next EMA questionnaire. To reduce participant burden, intentions, self-efficacy, and outcome expectations were programmed to appear in 40% of the EMA questionnaires. In addition to pro- viding EMA data, participants were also asked to wear an accelerometer on their waist during all waking hours (except when bathing or swimming) during each burst. At the conclusion of each burst, participants returned the study equipment. All study procedures were approved by the local Institutional Review Board.

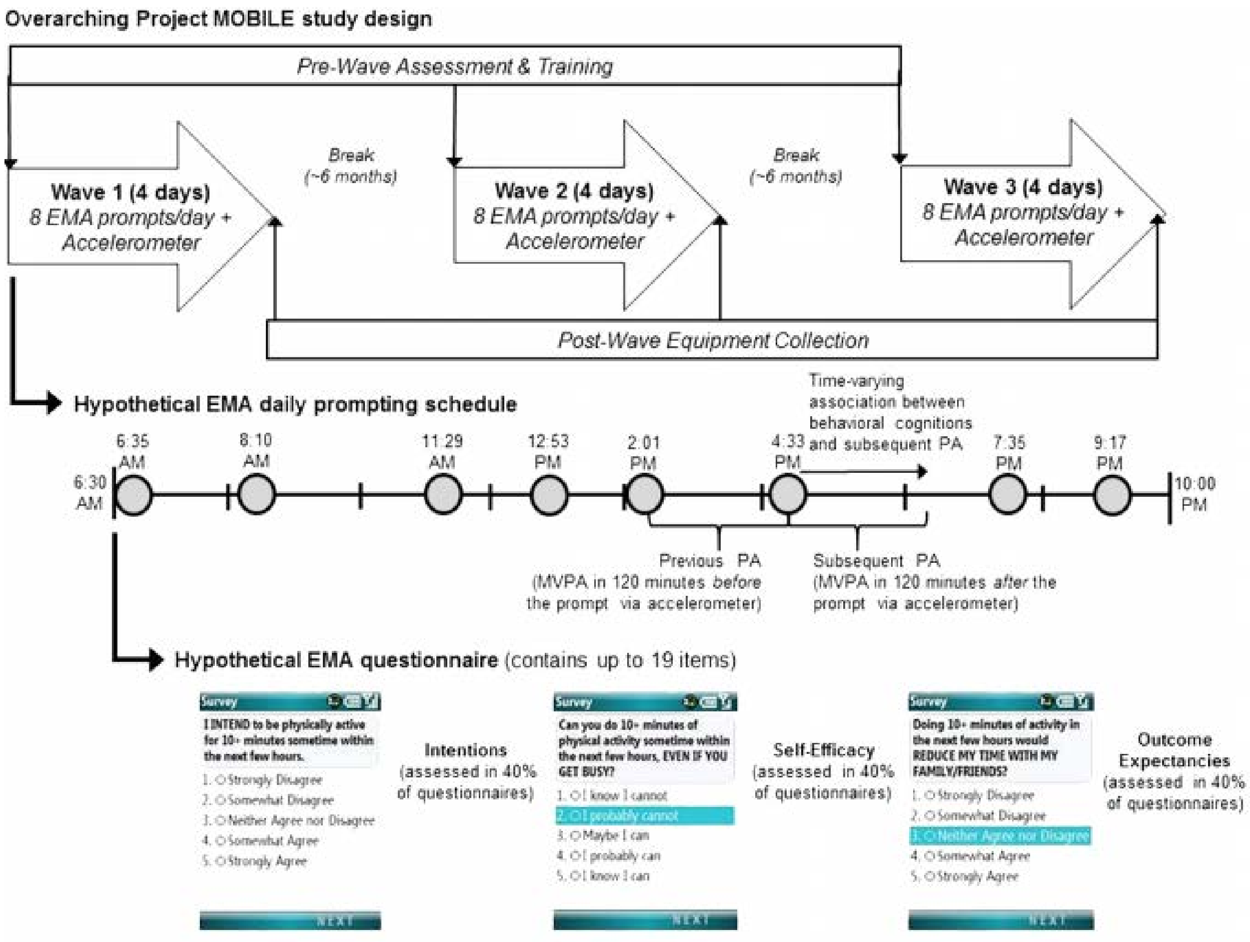

Figure 1 — Schematic of the Project MOBILE study design. PA = physical activity; MVPA = moderate- or vigorous-intensity physical activity.

Measures

Behavioral Cognitions. All behavioral cognitions items focused on 10+ min of physical activity to reflect the U.S. Federal Physical Activity Guidelines' recommendation that activity be accrued in bouts of at least 10 min (Physical Activity Guidelines Advisory Committee, 2008). *Intentions* to engage in physical activity were assessed using a single item (i.e., "I INTEND to be physically active for 10+ min sometime within the next few hours"; Pickering et al., 2016). Participants rated the item on a 1 (*strongly disagree*) to 5 (*strongly agree*) scale. *Self-efficacy* for engaging in physical activity was assessed through two items and focused on overcoming barriers to engaging in activity: "Can you do 10+ min of physical activity sometime within the next few hours EVEN IF YOU START TO FEEL TIRED?" and ". . . EVEN IFYOU GET BUSY?" (Pickering et al., 2016). Participants rated the items on a 1 (*I know I cannot*) to 5 (*I know I can*) scale. Accounting for within-person dependencies in ratings and allowing for heterogeneous factor loadings (Geldhof, Preacher, & Zyphur, 2014), responses were internally consistent ($\Omega = 0.84$), so a composite score was created by aver- aging responses together. *Outcome expectations* for engaging in physical activity were assessed with four items about the benefits and consequences of physical activity (i.e., “Doing 10+ min of activity in the next few hours would HELP ME FEEL LESS STRESSED”; “Doing 10+ min of activity in the next few hours would FEEL MORE ENERGETIC”; Pickering et al., 2016). Participants rated the items on a 1 (*strongly disagree*) to 5 (*strongly agree*) scale. Two items were reverse coded (i.e., “Doing 10+ min of activity in the next few hours would REDUCE MY TIME WITH FRIENDS AND FAMILY”; “Doing 10+ min of activity in the next few hours would MAKE ME FEEL TOO TIRED TO DO MY DAILY WORK”). Accounting for within-person dependencies in ratings and allowing for heterogeneous factor loadings (Geldhof et al., 2014), responses had fair internal consistency (Ω = 0.51); however, after removing an item (i.e., “Doing 10+ min of activity in the next few hours would REDUCE MY TIME WITH FRIENDS AND FAMILY”), internal consistency improved (Ω = 0.62), so a composite score was created by aver- aging responses from the remaining three outcome expectation items.

Physical Activity. Physical activity was objectively measured using an accelerometer-based activity monitor (Actigraph Model GT2M, firmware v06.02.00, Pensacola, FL). Time spent engaging in moderate- or vigorous-intensity physical activity (MVPA) was collected in 30-s epochs. The MVPA threshold was 2,020 counts per minute (equivalent to three metabolic equivalents). Subsequent physical activity was operationalized as total minutes of MVPA in the 2 hr following the completion of an EMA questionnaire, and previous physical activity was operationalized as total minutes of MVPA in the 2 hr before competition of an EMA prompt. Physical activity was operationalized as minutes of MVPA within 2-hr windows before and after EMA prompts to correspond with (a) definitions and examples of physical activity provided to participants and (b) the time frame of the next few hours in behavioral cognition items. Periods of 60 min of consecutive zero activity counts were considered accelerometer nonwear (15). Two-hr windows that contained less than 60 min of accelerometer wear were excluded from the data analysis.

Data Preparation

Power law transformations were conducted on any variable with a skewed distribution using the Box–Cox method (Box & Cox, 1964; Osborne, 2010). The Box– Cox method examines a series of power law transformations that will optimally normalize many skewed distributions (Box & Cox, 1964), eliminating the need to randomly try different transformations to determine the best transformation option (Osborne, 2010).

Data Analysis

The time-varying associations between physical activity and behavioral cognitions were examined using TVEM. TVEM explicitly models changes in the association between covariates and an outcome, both of which are intensively sampled over time in a flexible manner (Tan, Shiyko, Li, Li, & Dierker, 2012). The pattern of the association is estimated from data and can follow a complex smooth nonlinear curve. TVEM can accommodate unequal spacing of observations and an unequal number of assessments across participants. Thus, TVEM is uniquely suited for analysis of time-stamped intensive longitudinal data collected through EMA.

Models were fit in SAS 9.3 using the P-spline estimation method (TVEM SAS Macro, 2015). The P-spline estimation method is one of two spline-based methods (the other being B-spline) available in TVEM (Tan et al., 2012). While there are advantages and disadvantages of each of these estimation methods (e.g., Eilers & Marx, 1996; Eilers, Marx, & Durban, 2015), the P-spline method was chosen as the estimation procedure for TVEM because of its flexibility and computational efficiency. The P-spline approach yields smooth parameter functions that capture the nuances of momentary fluctuations without overfitting the model to the data. This is done by splitting a complex function into numerous segments, each of which is estimated with a polynomial model. Although a model can be perfectly fitted by specifying a large enough number of splitting points (referred to as knots in TVEM), specifying too many knots may introduce too much variance into the model, causing the outcome curves to become excessively wiggly (known as overfitting). On the other hand, specifying too few knots could fail to capture the true nuances within the data of time-varying associations, resulting in an extremely smooth curve (known as underfitting). As a result, when specifying the P-spline method within TVEM, the number of knots is automatically selected to control model complexity for the coefficient functions by a maximum likelihood approach (Tan et al., 2012). Technical details of model fitting can be found elsewhere (Li et al., 2015; Shiyko, Lanza, Tan, Li, & Shiffman, 2012; Shiyko, Naab, Shiffman, & Li, 2014; Tan et al., 2012).

To describe the average level of MVPA and behavioral cognitions over the course of the day, TVEM were run that predicted the outcome variable (either physical activity or a behavioral cognition) with only an intercept function ($\beta 0(tij)$) and error term (eij).

Subsequently, TVEM tested time-varying associations between behavioral cognitions measured at any given EMA prompt and subsequent change in MVPA. The below equation represents the model that was fit to the data to determine the course of variation in the association between intentions and subsequent MVPA across the day, where $SubsequentPhysicalActivity_{ij}$ represents MVPA in the 2 hr following the completion of an EMA prompt for each person i assessed at unique time point j. Parameters β_0 through β_4 represent parameter functions that change values depending on time of day (t). $\beta_0(t)$ serves as the intercept function that summarizes the average level of MVPA over the course of the day (i.e., from 6:30 a.m. to 10:00 p.m.) for men with the average BMI of the sample with no intentions to engage in physical activity, no MVPA in the 2 hr before the EMA prompt on a weekday. $\beta_1(t)$ represents the time-varying association between intentions to engage in physical activity and subsequent MVPA at any given EMA prompt j. $\beta_2(t)$ represents the time-varying-effect of weekend days (coded as a dummy variable). $\beta 3(t)$ represents the difference of the effect of intentions on weekend days relative to weekdays. $\beta 4(t)$ represents the time-varying association between previous and subsequent MVPA. Controlling for previous MVPA allows for the interpretation of the outcome as subsequent *change* in MVPA. Gender and BMI (grand- mean centered) were included as time-invariant covariates in the model. Therefore $\beta 5$ and $\beta 6$ represent traditional regression weights. The random errors, eij, are assumed to be normally distributed.

Dummy coded variables representing the measurement burst in the study as well as interaction terms between behavioral cognitions and dummy-coded burst variables were initially included in the TVEM described above; however, none of these terms were associated with subsequent physical activity. Age was also included in initial models as a time-invariant covariate, but it was not a significant predictor of subsequent physical activity in any model. Therefore, the more parsimonious models are presented.

Changes in the associations between behavioral cognitions and subsequent physical activity across the day were modeled between 6:30 a.m. and 10:00 p.m. as, because of the sampling protocol, this window represents the time during which behavioral cognitions could have been assessed. Any time period where behavioral cognitions significantly predicted subsequent physical activity reflects the times that behavioral cognitions were assessed.

RESULTS

Data Availability and Compliance

Of the 116 participants, 90 (78%) had three bursts of data, 11 (9%) had two bursts of data, and 15 (13%) had one wave of data. On average, participants responded to 83% (range = 46–100%) of delivered EMA prompts. This resulted in 7,910 EMA observations ($M = 68.19$, $SD = 22.20$, range = 10–96 per participant over 12 days). EMA compliance differed across several temporal factors. Compliance was higher during Measurement Burst 3 (87%) compared with Measurement Burst 1 (82%; $\beta = 0.32$, $SE = 0.113$, $p < .01$). In addition, participants had higher compliance responding to EMA prompts on week- days (85%) compared with weekend days (82%; $\beta = 0.20$, $SE = 0.08$, $p < .05$) and higher compliance responding to EMA prompts during the afternoon (i.e., noon–6:00 p.m.; 85%) compared with the morning (i.e., 6:30 a.m.–noon; 82%; $\beta = 0.25$, $SE = 0.08$, $p < .01$). Compliance also differed according to participants' BMI. Participants with higher BMI scores had lower compliance responding to EMA prompts ($\beta = 0.03$, $SE = 0.01$, $p = .020$).

$$\begin{aligned} SubsequentPhysicalActivity_{ij} = \beta_0(t) + \beta_1(t) * Intentions_{ij} + \beta_2(t) * Weekend_{ij} + \\ \beta_3(t) * Intentions \times Weekend_{ij} + \beta_4(t) * PreviousPhysicalActivity_{ij} \\ + \beta_5 * Gender_i + \beta_6 * BMI_i + e_{ij} \end{aligned} \quad (1)$$

Accelerometer compliance also differed across several temporal factors. Participants were more likely to have missing accelerometer data surrounding EMA prompts during Measurement Burst 1 compared with Measurement Burst 2 ($\beta = 0.70$, $SE = 0.04$, $p < .01$) and Measurement Burst 3 ($\beta = 0.01$, $SE = 0.001$, $p < .01$). In addition, participants were more likely to have missing accelerometer data on weekend days compared with weekdays ($\beta = 0.65$, $SE = 0.06$, $p < .01$) and more likely to have missing accelerometer data in the morning (i.e., 6:30 a.m.–noon) compared with the afternoon (i.e., noon–6:00 p.m.; $\beta = 0.49$, $SE = 0.28$, $p < .01$) and evening (i.e., after 6:00 p.m.; $\beta = 0.14$, $SE = 0.16$, $p < .01$).

Items assessing behavioral cognitions were delivered to participants on 40% of the EMA questionnaires. This resulted in 3,032 valid observations of intentions, 3,032 valid observations of self-efficacy, and 3,094 valid observations of outcome expectations. These valid observations were used to run TVEM to describe the average level of physical activity and behavioral cognitions over the course of the day. After taking into account accelerometer non- wear, there were 1,238 observations with valid intention and physical activity data, 1,217 observations with valid self-efficacy and physical activity data, and 1,256 observations with valid outcome expectation and physical activity data. These valid observations were used to run TVEM to test time-varying associations between behavioral cognitions and subsequent change in physical activity. The distribution of valid observations of behavior cognitions and physical activity across the day are displayed in Figure 1 of the supplementary file attached to the PDF of the online version of this article.

Descriptive Statistics

Ignoring clustering within individuals, participants accumulated an average of 2.55 min of MVPA per 2-hr window on weekdays (*SD* = 5.93, range = 0–111) and 2.20 min of MVPA per 2-hr window on weekend days (*SD* = 4.78, range = 0–95). Minutes of MVPA was significantly positively skewed on both weekdays and weekdays as indicated by a Shapiro–Wilk's test (ps < .001; Shapiro & Wilk, 1965). Therefore, the Box–Cox method was used to determine the optimal power law transformation to normalize the distribution of physical activity (Box & Cox, 1964; Osborne, 2010). Trans- formed MVPA values were used to estimate correlations and TVEM testing associations between behavioral cognitions and subsequent physical activity across the day. Raw MVPA values were used for TVEM describing the average level of physical activity over the course of the day.

Ignoring clustering within individuals, participants on average reported moderate levels of intentions ($M_{\text{week- day}}$ = 2.95, *SD* = 1.32; M_{weekend} = 3.01, *SD* = 1.33), self- efficacy (M_{weekday} = 3.31, *SD* = 1.42; M_{weekend} = 3.45, *SD* = 1.34), and outcome expectations (M_{weekday} = 3.58, *SD* = 0.83; M_{weekend} = 3.58, *SD* = 0.87) for physical activity at any given EMA prompt on both weekend days and weekdays. Only self-efficacy significantly differed by weekday and weekend day, with higher self-efficacy on weekend days compared with weekdays (t = 2.72, p = .01).

Bivariate correlations were estimated for descriptive purposes. At the prompt level, within-person correlations revealed that intentions (r_{weekday} = –.04, p = .71; r_{weekend} = –.07, p = .47), self-efficacy (r_{weekday} = .09, p = .35; r_{weekend} = .02, p = .83), and outcome expectancies (r_{weekday} = .01, p = .92; r_{weekend} = –.01, p = .98) had weak but nonsignificant correlations with subsequent physical activity. Behavioral cognitions had weak to moderate positive correlations with one another on both weekdays and weekend days. The strongest and weakest correlations among behavioral cognitions on both weekdays and weekend days were between intentions and self-efficacy (r_{weekday} = .55, p < .01; r_{weekend} = .40, p < .01) and self- efficacy and outcome expectations (r_{weekday} = .06, p = .51; r_{weekend} = .14, p = .14), respectively.

Time-Varying Levels of Physical Activity and Behavioral Cognitions on Weekdays and Weekend Days

To describe the average level of MVPA and behavioral cognitions over the course of the day, TVEM was run that predicted the outcome variable (i.e., either MVPA or one of the behavioral cognitions) with only an intercept function ($\beta 0(tij)$) and error term (eij). Figure 2 displays how the levels of MVPA and behavioral cognitions vary within a day (Panels A–C); the black curve represents weekdays and the gray curve represents weekend days. The average level weekday of MVPA peaked at approximately 9:20 a.m. and decreased through the late morning and early afternoon, upon which MVPA levels increased and peaked again at 5:05 p.m. and then decreased throughout the rest of the day. Weekend-day MVPA followed a quadratic trajectory. The average level of MVPA increased throughout the morning, peaking at approximately 1:05 p.m., and then decreased through- out the rest of the day. On weekdays, intentions were highest during the early morning (before 7:05 a.m.) and then declined over the course of the day. Intentions on weekend days were high and relatively stable through the morning and early afternoon. At approximately 1:05 p.m. on weekend days, intentions began declining sharply and continued to decline until the end of the day. Self-efficacy on weekdays was relatively stable until approximately 4:55 p.m., when efficacy began declining sharply. Self-efficacy on weekend days followed a quadratic shape, increasing through the morning until approximately 10:45 a.m., after which self-efficacy decreased slowly until approximately 5:05 p.m., when the rate of decline increased. Outcome expectations across both weekdays and weekend days were highest during the early morning (before 7:00 a.m.) and then declined over the course of the day.

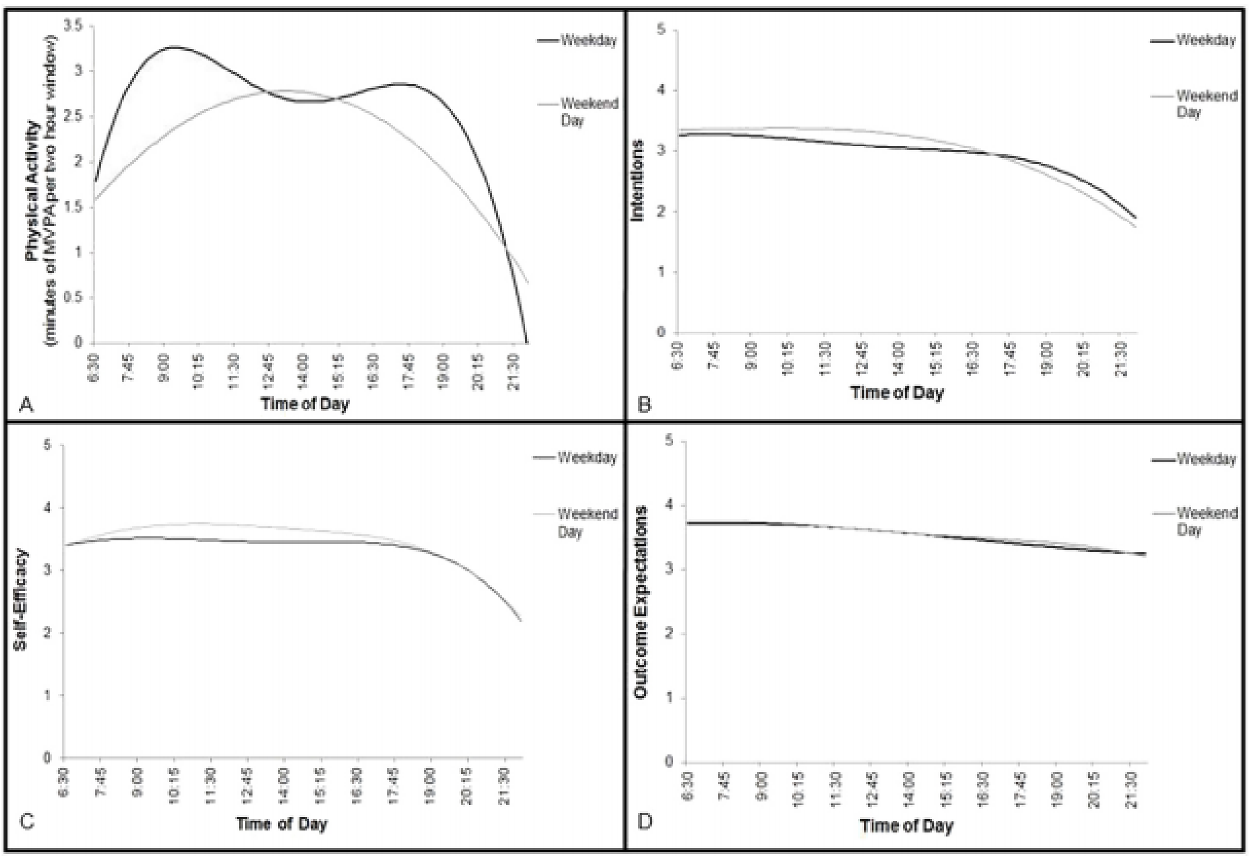

Figure 2 — Graphical summary of interception functions of average physical activity (minutes of moderate- or vigorous-intensity physical activity [MVPA] measured across the 2 hr after any given Ecological Momentary Assessment [EMA] prompt) and behavioral cognitions (measured at any given EMA prompt) across the day on weekdays (black curves) and weekend days (gray curves). In all panels, the *x*-axis represents time of day. Panel A represents the average level of physical activity on weekdays and weekend days as a function of time of day. Panel B represents the average level of intentions on weekdays and weekend days as a function of time of day. Panel C represents the average level of self-efficacy on weekdays weekend days as a function of time of day. Panel D represents the average level of outcome expectations on weekdays and weekend days as a function of time of day. Confidence intervals are not displayed in any panel; however, confidence intervals in all panels were above zero across the day. Figures are based on raw data.

Time-Varying Effects of Behavioral Cognitions on Physical Activity on Weekdays and Weekend Days

To test the time-varying associations between behavioral cognitions and subsequent physical activity on weekdays and weekend days, TVEM was run as described in the equation above. Figure 3 shows the time-varying associations between behavioral cognition variables at any given EMA prompt and subsequent change in MVPA measured over the next 2 hr after that EMA prompt for weekdays (Panels A–C) and weekend days (Panels D–F). The associations between behavior cognitions and subsequent physical activity are plotted separately so that trends for both weekday and weekend days are clear. The significant time windows specified in these results reflect the times that behavioral cognitions were assessed. Results from TVEM revealed that intentions positively predicted change in subsequent physical activity in the morning (9:25 a.m.–11:45 a.m.) and in the evening (8:15 p.m.–10:00 p.m.) but not at any other time on weekdays. These findings are represented by the functions above the zero line in Figure 3 (Panel A) with magnitudes ranging from $\beta = 0.05–0.06$ in the morning and $\beta = 0.06–0.14$ in the evening. On weekend days, intentions did not positively predict change in subsequent physical activity at any time. On weekdays, self-efficacy positively predicted change in subsequent physical activity in the evening (7:35 p.m.–10:00 p.m.) at magnitudes ranging from $\beta = 0.09–0.25$. Self-efficacy did not predict change in sub- sequent physical activity at any other time on weekdays. On weekend days, self-efficacy was unrelated to change in subsequent physical activity across the day. On both weekdays and weekend days, outcome expectations were unrelated to change in subsequent physical activity across the day. Ultimately, the shapes of the curves on weekdays and weekend days were not statistically different as rep- resented by the overlapping confidence intervals of the depicted slope curves.

Previous physical activity, which served as a time- varying covariate in each TVEM and allowed for the interpretation of the outcome as subsequent *change* in physical activity, was positively associated with subsequent physical activity for the majority of the day. A more detailed description regarding the time-varying effect of previous physical activity across each behavior cognition model is shown Figure 2 of the supplementary material. Concerning time-invariant control variables, across all models (a) men tended to engage in more MVPA com- pared with women and (b) BMI was unrelated to MVPA.

DISCUSSION

This study provides evidence that associations between behavioral cognitions and subsequent physical activity are dynamic, changing over the course of the day on weekdays. Previous research shows that behavioral cognitions at any given moment or day are related to corresponding levels of the physical activity at those same or subsequent points in time (Conroy, Elavsky, et al., 2013; Conroy et al., 2011; Pickering et al., 2016). However, that work made the assumption that behavioral cognitions uniformly influence physical activity across the day or across days. The current study extends this work by demonstrating that the strength of those associations may change over the course of the day. Specifically, on weekdays, intentions were associated with subsequent physical activity in the morning and evening, and self-efficacy was associated with subsequent physical activity in the evening on weekdays. However, on weekdays, outcomes expectancies were unrelated to physical activity throughout the day. On weekend days, none of the behavioral cognitions were significantly associated with subsequent physical activity regardless of time of day. Thus, results from this study suggest that motivation-based physical activity interventions may benefit from delivering intervention content at specific times during the day in a “just-in-time” fashion to optimize behavior change.

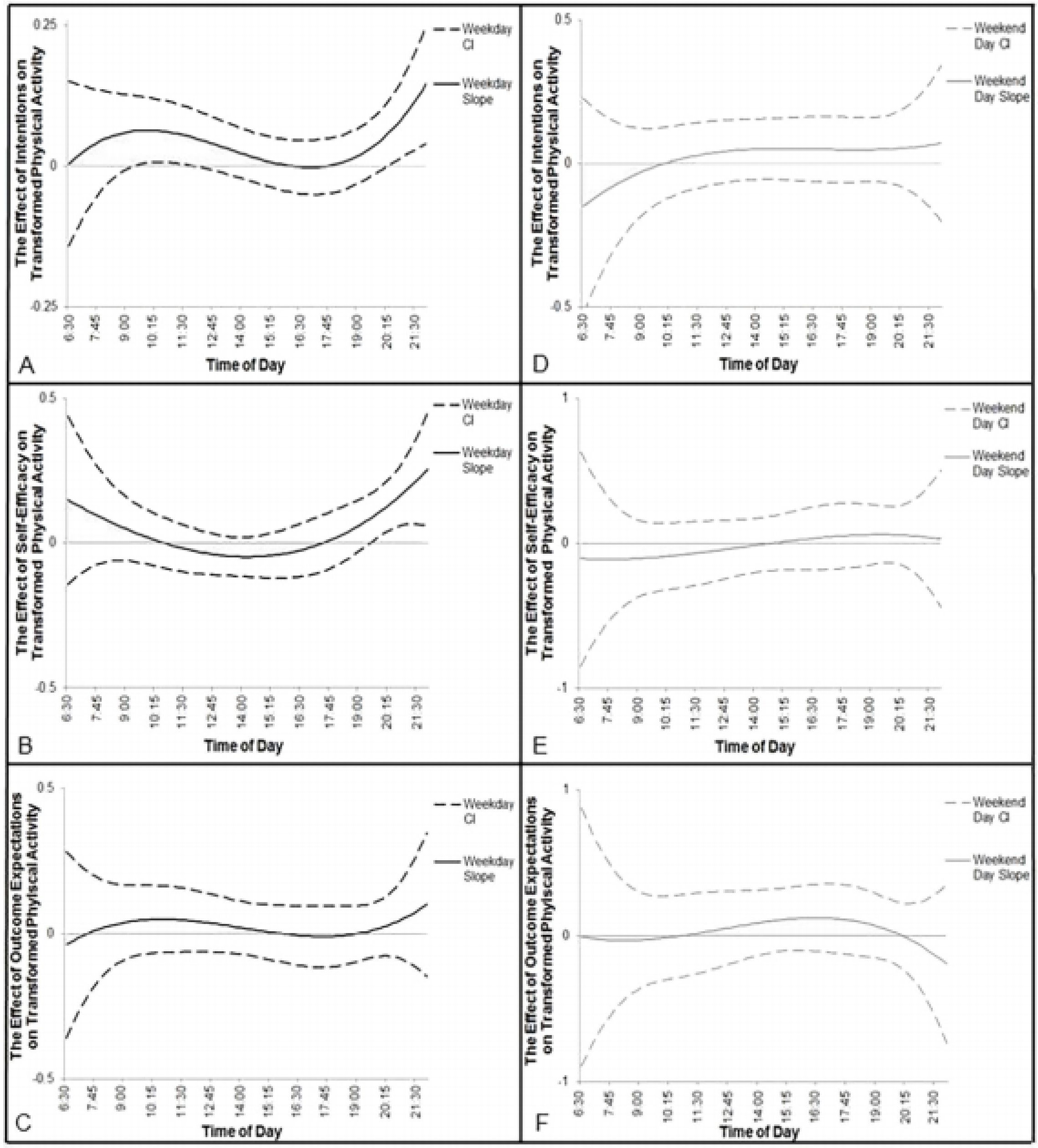

Figure 3 — Graphical summary of slope function. In the panels on the left, the *y*-axis represents the magnitude of the time-varying associations between intentions (Panel A), self-efficacy (Panel B), and outcome expectancies (Panel C) at any given EMA prompt and subsequent physical activity across the next 2 hr after that prompt on weekdays. In the panels on the right, the *y*-axis represents the magnitude of the time-varying associations (unstandardized coefficients) between intentions (Panel D), self-efficacy (Panel E), and outcome expectancies (Panel F) at any given EMA prompt and subsequent physical activity across the next 2 hr after that prompt on weekend days. The *x*-axis represents time of day across in all panels. Any point where the slope and confidence intervals are all above or below the zero line represents statistically significant positive or negative associations, respectively, at that particular time of day. Each time-varying effect model controlled for physical activity across the 2 hr before the prompt, sex, and body mass index. CI = confidence interval.

Consistent with previous research examining within- person processes, intentions and self-efficacy were positively related to subsequent change in physical activity in this study (Conroy, Elavsky, et al., 2013; Conroy et al., 2011; Pickering et al., 2016) whereas outcome expectations were unrelated to subsequent change in physical activity (Pickering et al., 2016). Unlike previous research examining within-person processes, this study revealed that when no parametric assumptions are placed upon the model, the strength of associations changes over the course of the day. This is the first known study to document such findings in the physical activity literature.

Contrary to our hypothesis, behavioral cognitions and subsequent change in physical activity were significantly associated in both the morning and the evening. On weekdays, intentions positively predicted behavior in the morning and evening and self-efficacy predicted behavior in the evening. Consistent with research on the self-regulation of behavior, behavioral cognitions tended to peak in the morning or early afternoon on both weekdays and weekend days. In addition, participants tended to engage in the most physical activity in the morning hours. It may be that the positive association between intention and physical activity in the morning is the results of high levels of self-regulatory resources at this time. As a result, individuals are better able to enact their intentions to engage in physical activity. During the evenings on weekdays, adults are likely to preserve this time for unwinding and relaxing after a long day of work- and household-related responsibilities through leisure activities like watching their favorite television program or reading an interesting book. Therefore physical activity may not be a high priority for adults in the evening. Indeed, the data from this study suggest that the evening hours between 7:00 p.m. and 10:00 p.m. reflect times of relatively low behavioral cognitions to engage in physical activity as well as low levels of physical activity (relative to the morning). Therefore, significant associations between behavioral cognitions and subsequent physical activity at this time are likely the result of a lack of motivation for physical activity and subsequently not engaging in the behavior.

Time-varying associations between behavioral cognitions and subsequent change in physical activity demonstrated a trend of weekday versus weekend-day differences. For example, intentions positively predicted subsequent change in physical activity in the morning and evening on weekdays but at no time on weekend days. The positive association between intentions and subsequent change in physical activity in the morning on weekdays but the absence of these associations at this time on weekend days may be the result of the predictability and routine of the workday (e.g., individuals must complete tasks while seated at a desk; Brownson, Boehmer, & Luke, 2005; Church et al., 2011; McCrady & Levine, 2009). Whereas on weekend days, adults’ schedules are likely to be less predictable and more flexible, causing an uncoupling between behavioral cognitions and subsequent behavior. Although these possible explanations are speculative, time use and context likely play an integral part in these time-varying associations (or lack thereof) between behavioral cognitions and subsequent change in physical activity on both weekdays and weekend days.

One of the main assumptions of social cognitive theory is that behavioral cognitions such as intentions, self-efficacy, and outcome expectations represent a gate- way to behavior change (Bandura, 1998). Many physical activity interventions are designed to promoted consistently high levels of behavioral cognitions; however, results from this study suggest there are specific times during the day when those cognitions and behavior are strongly coupled and other times when these cognitions are unrelated to behavior. Exploring time-varying associations between determinants, motivational and otherwise, and subsequent health behaviors has the potential to inform the development of just-in-time interventions so that content is delivered at the time when, for example, having strong intentions is likely to result in physical activity (i.e., a window of opportunity). On the other hand, this line of research could inform when not to deliver certain content, for example, when intentions are not likely to translate into behavior (i.e., a window of vulnerability). In such instances, other motivational content, such as action or coping planning, may be delivered to facilitate the translation of intentions into behavior (Schwarzer et al., 2007).

Taking a more nuanced approach to understanding behavior, as was done in this study by capturing individuals' motivation and behavior as it unfolds in the context of daily life, is likely the most promising way to understand human behavior as well as mechanisms of change and, thus, develop effective interventions. This work also points to the need for future work to examine time-varying reciprocal relationships between motivation and behaviors through dynamical systems modeling or other novel quantitative approaches, as there may be feedback loops linking changes in behavior with subsequent changes in motivations, which may in turn lead to further changes in behavior across the day (Rivera, Pew, & Collins, 2007).

Finally, results from this study suggest that the dynamic nature of behavior and behavioral cognitions needs to be incorporated into physical activity theories of motivation (Rhodes & Nigg, 2011; Sniehotta et al., 2014). As evidence continues to accumulate regarding these time-varying processes, it only further emphasizes that traditional theories of motivation that focus exclusively on between-persons determinants of behavior are missing important information as to how associations between behavioral cognitions and behavior unfold naturally in the context of everyday life (Conroy, Elavsky, et al., 2013; Conroy et al., 2011; Pickering et al., 2016). This absence of information regarding time-varying processes has likely contributed to the limited predictive power of many popular theories of motivation (McEachan, Conner, Taylor, & Lawton, 2011; Rhodes & Dickau, 2012).

The current study is not without limitations. The sample was fairly homogeneous with respect to sex and employment status. Future research should include greater numbers of men as well as individuals who are unemployed or have nontraditional work schedules as these factors may influence time-varying associations between behavioral cognitions and physical activity (Church et al., 2011; Martin et al., 2014). There may be gender differences in time-varying associations between behavioral cognitions and physical activity, and this topic remains an important direction for future research. Moreover, it is unclear whether employed individuals in the sample had blue-collar or white-collar occupations, which may also affect relations between behavioral cognitions and physical activity across the day. In addition, this sample focused specifically on adults age 25 and older, and results may differ for adolescents, college students, and older adults. In the current study, study days were aggregated into weekdays and weekend days. It is possible that the trajectories of physical activity and behavioral cognitions as well as time-varying associations between them differed across specific weekdays and weekend days. The EMA measures used in this study were adapted from theoretical constructs to reflect momentary behavioral cognitions as well as to fit within the display screen. As the popularity of EMA studies continues to grow, future research should focus on validating measures employed in these types of studies. Moreover, behavioral cognition items emphasized the target behavior as engaging in at least 10 min of physical activity in the next few hours. The interpretation of this exact time frame was left up to the individual, potentially confounding results. In addition, because of low levels of physical activity across the sample, we were unable to examine associations between behavioral cognitions and subsequent bouts of physical activity lasting 10 min or longer. Furthermore, because participants missed EMA prompts and did not wear the accelerometer when sleeping, there tended to be fewer valid observations at the beginning of the day compared with the afternoon or evening—resulting in wider confidence intervals at the left tail of the function curves. Our missing data analysis also revealed that participants were also less likely to have valid observations on weekend days compared with weekdays. Null associations on weekday mornings between behavioral cognitions (i.e., self-efficacy and outcome expectations) and subsequent physical activity as well as null associations on weekend days may have been affected by lower levels of compliance with study procedures at those times. Therefore future research should aim to further investigate time-varying associations between behavioral cognitions and subsequent physical activity on weekday mornings and weekend days. Moreover, there may be other time-varying (e.g., affect, physical and social context) and time-invariant (e.g., implicit attitudes, habits) influences that could be associated with physical activity at specific times during the day or across the day that were beyond the scope of this study (Conroy, Hyde, Doerksen, & Ribeiro, 2010; Conroy, Maher, Elavsky, Hyde, & Doerksen, 2013; Dunton et al., 2014; Dunton, Kawabata, Intille, Wolch, & Pentz, 2012; Liao, Intille, & Dunton, 2015; Maher & Conroy, 2016). Regarding the estimation methods, to counter overfitting of the data due to a large number knots, the P-spline estimation method uses a penalty (through the use of a mixed-effect model) whereas the B-spline approach requires the user to manually fit the number of knots based on Akaike information criterion and Bayesian information criterion fit statistics (Li et al., 2015). As a result, it is possible that the P-spline method can yield smoother estimates of the coefficient functions compared with B-spline; however, we tested TVEM models using both estimation methods and the results were consistent across both methods. In addition, spline-based methods use a global smoothing parameter that can lead to the smoothness of the curves remaining virtually the same across time (Wahba, 1990). While there is currently not a way to account for changing roughness in the curves using TVEM, future iterations of the TVEM macro should explore the use of adaptive smoothing splines where the smoothing parameter can vary across time (Liu & Guo, 2010; Wang, Du, & Shen, 2013). Finally, there were a limited number of observations where there were valid data for all three behavioral cognitions and physical activity before and after the prompt ($n_{\text{observations}}$ = 203). Because of the small number of observations, we were unable to conduct TVEM simultaneously entering all three behavior cognitions and interactions to explore weekday/weekend-day differences in the time-varying associations.

In conclusion, this study used intensive longitudinal data collected through EMA to investigate the time- varying associations between behavioral cognitions and physical activity. This study is the first of its kind in yielding results that suggest temporal variation in the associations between behavioral cognitions and subsequent physical activity that would otherwise be overlooked with traditional linear data analytic methodologies. By establishing that the relationships between behavioral cognitions and physical activity are dynamic across the day in natural settings, this study identifies windows of opportunity and vulnerability for motivation-based physical activity interventions.

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