Momentary assessment of physical activity intention-behavior coupling in adults

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Abstract:

Research attempting to elucidate physical activity (PA) intention-behavior relations has focused on differences in long-term behavior forecasting between people. However, regular PA requires a repeated performance on a daily or within-daily basis. An empirical case study application is presented using intensive longitudinal data from a study of PA in adults to (a) describe the extent to which short-term intention-behavior coupling occurs and (b) explore time-varying predictors of intention formation and short-term intention-behavior coupling. Adults ($n = 116$) participated in three 4-day waves of ecological momentary assessment (EMA). Each day, participants received EMA questionnaires assessing short-term PA intentions and wore accelerometers to assess whether they engaged in ≥10 min of moderate-to-vigorous physical activity (MVPA) in the 3-hour period after each EMA prompt. Concurrent affective states and contexts were also assessed through EMA. Participants reported having short-term intentions to engage in PA in 41% of EMA prompts. However, participants only engaged in ≥10 min of MVPA following 16% of the prompts that short-term PA intentions were reported indicating an intention-behavior gap of 84%. Odds of intentions followed by PA were greater on occasions when individuals reported higher levels of positive affect than was typical for them. This study is the first to take an EMA approach to describe short-term intention-behavior coupling in adults. Results suggest that adults have difficulty translating intentions into behavior at the momentary level, more so than over longer timescales, and that positive affect may be a key to successfully translating intentions into behavior.

Keywords: Intention-behavior gap | Exercise | Planned behavior | Motivation

Article:

Implications

Researchers: While time-varying factors such as affect and time of day contribute to short-term physical activity intention-behavior coupling, more research is needed to explore other time-varying factors including characteristics of the physical environment and self-regulation.

Practitioners: Healthcare providers should recognize that intentions will not always translate into behavior depending on the current context and encourage patients to study and recognize the contexts that are most conducive to following through with short-term physical activity intentions.

Policymakers: Resources should be directed towards novel methodological approaches designed to better understand the processes influencing health behaviors in the context of everyday life.

Intentions to engage in physical activity (PA) are posited as a proximal determinant of behavior in many popular theories of motivation [1, 2]. Yet, the predictive power of intentions to explain PA behavior is often limited in empirical studies [3, 4]. Previous research has almost exclusively focused on identifying time-invariant predictors of why some people have stronger intentions than others (i.e., intention formation) or are better able to follow-though with their intentions than others (intention-behavioral coupling) [5, 6]. Studies in this area often focus on long-term intentions such as intentions to engage in regular PA over time spans up to several months. As a result, it is unclear what time-varying factors predict intentions to be active and intention-behavior coupling over shorter time frames such as minutes and hours, which may be important for understanding why individuals fail to engage in PA that was intended just a few hours earlier. This article describes methods for using intensive longitudinal data (IDL) collected through ecological momentary assessment (EMA) as well as accelerometery to investigate short-term intentions to be active and intention-behavior coupling in adults.

Even though individuals may form intentions to be active, evidence suggests it can be difficult to translate those intentions into behavior. As many as 46% of individuals may fail to follow through with their long-term intentions regarding PA [7]. Therefore, understanding the factors that inhibit or facilitate intention-behavior coupling is warranted. A recent review of 57 studies found that people’s behavioral cognitions such as self-efficacy (i.e., beliefs about one’s abilities regarding PA) and affective attitudes (i.e., perceived enjoyment of performing PA), but not instrumental attitudes (i.e., perceived utility of PA), contribute to intention-behavior coupling [6]. Similar findings were replicated in a second review focusing exclusively on intention-behavior discordance [5].

While these lines of research certainly help to elucidate intention-behavior relations, the studies included in these reviews tend to look at long-term behavior forecasting (i.e., adopting or maintaining a regular pattern of behavior over several months). However, regular PA requires a repeated performance on a daily or within-daily basis. In fact, the US federal physical activity guidelines note that the recommended levels of PA (i.e., 150 min of moderate- or 75 min of vigorous-intensity physical activity [MVPA] per week) can be accumulated in as little as 10-min bouts of activity, which allow for multiple accumulated bouts of PA across a day [8].

Understanding the motivational processes behind decisions to engage in a given bout of PA is necessary to promote more frequent bouts as well as greater total volume of PA among low-active individuals.

There may be time-varying factors such as time of day, how one feels, or where one is that explain the formation and enactment of short-term PA intentions over timescales as short as a few hours, that when stringed together may explain an overall pattern of behavior in those hours. Moreover, these time-varying factors may be poorly captured in long-term forecasts. For example, being outside may be more conducive to following through with short-term intentions to engage in PA (strengthening intention-behavior coupling) whereas being indoors may serve as a barrier to following through with short-term intentions (lessening intention-behavior coupling). Indeed, adults are more likely to engage in PA at times when they are outdoors compared to indoors [9]. It may be that intentions and intention-behavior relations change as a result of a variety of time-varying factors. Engaging in regular PA is likely to be a mix of long-term (e.g., "I want to be regularly active") and short-term goals (e.g., "I need to be active today to fulfill my goal of being regularly active") [2]; however, our understanding of intention-behavior relationships has tended to focus on more long-term associations. Such a focus on long-term forecasting may miss momentary and contextual factors important to the day-to-day or hour-to-hour processes of intention formation and translating intentions into behavior.

EMA is a real-time data capture strategy [10] that may be particularly well suited to address the potential limitations of previous research investigating intention formation and intention-behavior coupling. EMA allows researchers to examine PA intentions over shortened timescales to understand how they might predict immediate behavior [10]. EMA can also reduce biases associated with forecasting intention and recalling behavior over long periods of time (e.g., weeks, months) [10]. Finally, EMA methods enhance ecological validity by measuring intentions and behavior in the settings where they naturally occur [10].

To date, a small number of studies have employed EMA to investigate short-term intentions as a predictor of subsequent PA as well as predictors of short-term intention strength [11, 12, 13]. For example, in a study investigating the influence of daily intentions on daily PA in college students, Conroy et al. [11] found that daily PA was associated with daily intentions, daily perceptions of limited time availability, and weekend status. Additionally, daily intentions were positively associated with average levels of self-efficacy and fatigue (i.e., a time-invariant association) as well as daily attitudes (i.e., instrumental and affective), daily injunctive norms, and daily self-efficacy for PA as well as daily perceptions of limited time and weekend status (i.e., time-varying associations). However, because this study focused on daily intention-behavior relations, it is unclear what time-varying factors predict intentions and intention-behavior coupling across shorter time frames such as a few hours, which may be important for understanding motivational and decision-making processes involved with performing multiple accumulated bouts of PA across the day. The role that these time-varying factors play in intention formation as well as intention-behavior coupling is necessary to understand the processes that regulate PA in the context of everyday life and ultimately develop more effective, tailored interventions for individual behavior change.

This article describes methods for using ILD collected through EMA and accelerometer to investigate short-term intention-behavior coupling. An empirical case study application is presented to provide an example from an EMA study of PA in adults to show how ILD can be used to (a) describe the extent to which short-term intention-behavior coupling occurs and (b) explore time-varying predictors of intention formation and short-term intention-behavior coupling. In this empirical case study, affective state, physical and social context, and temporal factors will serve as time-varying predictors of intention formation and short-term intention-behavior coupling.

METHODS

Participants

This study was a secondary data analysis from a longitudinal study, Project MOBILE (Measuring Our Behaviors in Living Environments), investigating the intrapersonal, interpersonal, and environmental influences on PA. Participants were recruited from a suburban community east of Los Angeles via flyers, mailers, and directly contacting individuals who had previously participated in research studies. Inclusion criteria were as follows: (a) age 25 years or older and (b) ability to access a smartphone while at work to complete electronic EMA questionnaires. Exclusion criteria were as follows: (a) did not speak and read English fluently, (b) had an annual household income greater than US $210,000, (c) regularly performed more than 150 min per week of exercise or PA, or (d) had a physical limitation that prevented exercise. High-income individuals or those meeting PA guidelines were excluded to focus on health behavior determinants in a sample of individuals that were at elevated risk for obesity. After screening, eligible participants were scheduled to attend an introductory session.

Procedures

Participants completed three separate 4-day measurement waves during which participants were prompted with eight EMA surveys per day and wore an accelerometer. Intervals between measurement waves varied, with an average interval between waves 1 and 2 of 6.4 months (SD = 1.6; range = 3.7–15.4 months) and the average interval between waves 2 and 3 of 6.1 months (SD = 1.9; range = 0.5–13.2 months). On average, participants completed the entire protocol over 12.5 months (SD = 1.9; range = 8.2–24.5 months).

At the beginning of each measurement period, participants attended an introductory session where they were familiarized with the study procedures and the equipment to be used in the study. Participants were provided with a waist-worn accelerometer and an HTC Shadow mobile phone (T-Mobile U.S.A., Bellevue, WA) to complete study procedures. Each mobile phone had a custom version of MyExperience software installed, which supported EMA data collection. The software was programmed to display electronic question sequences and response choices on the mobile phone. During each measurement period, participants answered eight prompts to complete brief EMA questionnaires over the course of each day. Each EMA prompt occurred randomly within one of eight preprogrammed windows between 6:30 am and 10:00 pm. When prompted, participants were instructed to complete the brief EMA questionnaire. Each EMA questionnaire included up to 19 items and took approximately 2 to 3 min to complete. If participants were engaged in an incompatible activity (e.g., driving, sleeping), they were instructed to ignore the prompt. After the initial prompting, if participants did not respond to the EMA prompt, the phone emitted up to three reminder signals at 5-min intervals. Following the third reminder, the EMA questionnaire was no longer accessible for that window. Participants were also asked to wear an accelerometer on their waist during all waking hours (except when bathing or swimming). Prior to leaving the introductory lab session, participants completed a questionnaire regarding demographic information and were measured for anthropometric data by a trained research assistant. Informed consent was obtained from all individual participants included in the study. All procedures were approved by the local Institutional Review Board.

Measures

Short-term intention

Intention to engage in PA was assessed using a single item (i.e., "I intend to be physically active for 10+ min sometime within the next few hours) [13]. Participants provided ratings on a 1 (*strongly disagree*) to 5 (*strongly agree*) scale. Midscale values were used to separate occasions when participants did not intend (value below or equal to midscale) versus occasions when participants did intend (value above midscale). This approach for dichotomizing ratings of intention is consistent with previous research on intention-behavior coupling [14, 15, 16]. This dichotomized approach represents intention as a decisional variable similar to stage algorithms [17] and what Ajzen and Fishbeing [18] refer to as intention choice. Intention was assessed in a randomly selected 40% of the EMA prompts given to each participant.

Physical activity

PA was objectively measured via an Actigraph GT2M accelerometer-based activity monitor (Firmware v06.02.00; Actigraph, Pensacola, FL). Accelerometer data was used to calculate the minutes of MVPA (i.e., ≥2020 activity counts per minute [19]) in the 3 h after the EMA prompt. Accelerometer data were screened for non-wear defined as 60 min of consecutive zero activity counts. Three-hour windows that contained less than 120 min of accelerometer wear were considered to be non-valid windows and excluded from the data analysis. While no current recommendations exist regarding the amount of wear needed to consider a window of time within a day to be valid, the 2 h of wear in a 3-h window (i.e., 66% valid wear) criterion was used to approximate the percentage of wear achieved by current recommendations of 10 h of wear across waking hours (approximately 16 h) to be considered valid day [19]. PA was operationalized as minutes of MVPA recorded in the 3 h after the EMA prompt to correspond with (1) the definition of PA provided to participants (i.e., definitions of moderate- and vigorous-intensity activities) and (2) the time frame specified in the intention item of a few hours. On occasions when participants accumulated ≥10 min of MVPA in the 3-hour window, they were considered to have engaged in PA. On occasions when participants accumulated < 10 min of MVPA in the 3-hour window, they were considered to have not engaged in PA.

Concurrent affect

Positive affect was assessed using three items focusing on current feelings of happy, cheerful, and relaxed (e.g., "How HAPPY were you just before the beep went off?") [20]. *Negative affect* was assessed using four items focusing on current feelings of stressed, angry, anxious, and depressed (e.g., "How STRESSED were you just before the beep went off?") [20]. *Energy* was assessed using a single item (e.g., "How ENERGETIC or FULL OF PEP were you just before the beep went off?") [20]. *Fatigue* was also assessed through a single item (e.g., "How FATIGUED or TIRED were you just before the beep went off?") [20]. Participants provided ratings for all affect items on a 1 (*not at all*) to 5 (*extremely*) scale. Responses to both the positive affect and negative affect items were internally consistent ($\alpha = 0.84$ and 0.87, respectively) and a composite score was created for each type of affect by averaging responses together. Each affect construct was assessed in a randomly selected 60% of EMA prompts given to each participant.

Concurrent context

Physical context was assessed by having participants report whether they were indoors or outdoors at the time of the EMA prompt [9]. *Social context* was assessed by having participants report whether they were alone or with others at the time of the EMA prompt [9]. Physical and social context were each assessed in a randomly selected 60% of EMA prompts given to each participant.

Temporal factors

Each EMA prompt was coded for the *time of day* that it occurred as morning (6:30 to 11:59 am), afternoon (12:00 to 5:59 pm), or evening (6:00 to 10:00 pm). *Day of week* of the EMA prompt was coded as weekend day or weekday.

Demographic characteristics

Participant's sex and income were self-reported as part of a questionnaire at the introductory session. Body mass index (BMI, kg/m^2) was determined via height and weight measurements by a trained research assistant at the introductory session.

Data analysis

To describe the extent to which short-term intention-behavior coupling occurs, frequency counts were used. Consistent with research that has used an action control framework to investigate intention-behavior coupling [14, 21], event categories were created based on whether or not participants intended to be active and whether or not they subsequently accumulated at least 10 min of MVPA in the 3-hour window after the EMA prompt. On occasions when participants intended to engage in PA, participants were categorized as subsequently engaging in PA (i.e., intentions followed by PA) or subsequently not engaging in PA (i.e., intentions followed by no PA). On occasions when participants did not intend to engage in PA, participants were categorized as subsequently engaging in PA (i.e., non-intentions followed by PA) or subsequently not engaging in PA (i.e., intentions followed by no PA). Using these event categories, three sets of multilevel logistic regressions were tested in Stata 14 using MELOGIT to identify the time-invariant and time-varying predictors of intentions to be active and intention-behavior coupling at the momentary level. For more information on multilevel logistic regression model specifications in Stata 14 use the command HELP MELOGIT.

Multilevel logistic regression models account for the nested structure of the intensive longitudinal data collected through EMA. Separate multilevel logistic regression models were run for each predictor. Between-subject (BS; level-2, time-invariant) and within-subject (WS; level-1, time-varying) versions of these predictor variables were generated (i.e., partitioning the variance) [22]. The BS version is grand mean-centered to represent the deviation of that individual from the group mean, and the WS version is person mean-centered to represent deviation of that observation from one's own mean [23]. Therefore, the WS (i.e., prompt-level) results can be interpreted as adjusted for BS (i.e., person-level) effects. Each multilevel logistic regression model controlled for sex, BMI, and income.

The first set of multilevel logistic regression models was tested to demonstrate how EMA data can be used to explore time-varying predictors of *intention formation* (i.e., occasions when participants intended to be physically active versus occasions when participants did not intend to be active). These analyses did not take into account participants subsequent PA. Instead, they only focused on whether an intention was formed or not. The second set of multilevel logistic regression models was tested to demonstrate how EMA data can be used to explore time-varying predictors of the coupling of intentions and behavior (i.e., occasions when intention were followed by PA versus occasions when intentions were not followed by PA). The third set of multilevel logistic regression models was tested to demonstrate how EMA can be used to explore time-varying predictors of the coupling of non-intention and non-behavior (i.e., occasions when non-intentions were not followed by PA versus occasions when non-intentions were followed by PA). As with the first set of multilevel models, separate models were tested for each predictor, predictors assessed through EMA were aggregated and person-centered to create BS and WS variables, and models controlled for sex, BMI, and income.

RESULTS

Participant characteristics

Participants were 116 community-dwelling adults (M_{age} = 40.3 years, *SD* = 9.6). The majority of the sample identified as female (74.2%). Participants were diverse with respect to race (46.6% Caucasian, 27.2% Asian, 8.7% Biracial/Mixed, 7.8% African American, 3.3% American Indian/Alaskan Native, 6.4% Other or choose not to identify). The sample was ethnically diverse with 30.3% Hispanic/Latino. Median household income in the sample was US $60,001 to $70,000. Participants were relatively evenly split between three BMI categories with 38.2% classified as underweight or normal weight, 30.9% classified as overweight, and 30.9% classified as obese. Based on accelerometer data, 75.6% of participants were not meeting PA guidelines (defined as 30+ min of MVPA/day at any point during the study).

Data availability and compliance

Regarding participants, slightly more than three-fourths (78%, *n* = 90) of participants had all three waves of data, 9% (*n* = 11) had only two waves of data, and 13% (*n* = 15) had only one wave of data. Regarding EMA observations, participants, on average, responded to 83% (range = 46–100%) of delivered EMA prompts. This resulted in 7910 EMA observations (M = 68.19, *SD* = 22.20, range = 10–96 per participant over 12 days). EMA compliance differed by several temporal factors. Compliance was higher during wave 3 (87%) compared to wave 1 (82%; β = 0.323, SE = 0.113, *p* = .006). Additionally, participants had higher compliance responding to EMA prompts on weekdays (85%) compared to weekend days (82%; β = 0.201, SE = 0.079, *p* = .013) and higher compliance responding to EMA prompts during the afternoon (i.e., noon–6:00 pm; 85%) compared to the morning (i.e., 6:30 am–noon) 82%; β = 0.251, SE = 0.080, *p* = .003). Compliance also differed by participants' BMI. Participants with higher BMI scores had lower compliance responding to EMA prompts (β = 0.027, SE = 0.012, *p* = .020).

Valid intention data was available in 3032 observations from 110 participants. After removing observations with accelerometer non-wear (i.e., less than two valid hours of PA data in the 3 h after the EMA prompt), there were 1393 with valid intention and MVPA data from 110 participants to be used in the analytic models. Of the observations eliminated due of accelerometer non-wear (*n* = 1639), 68% (*n* = 1115) had zero activity counts accumulated in the 3-hour window after the prompt suggesting that participants were not wearing the activity monitor at all during that time, 11% (*n* = 180) of observations eliminated had less than 1 hour of valid wear, and 21% (*n* = 344) of observations eliminated had more than 1 hour but less than 2 hour of valid wear. Additionally, nearly 40% (*n* = 643) of the observations eliminated due to non-wear occurred during either the first (i.e., at 6:30 am) or last prompt (i.e., between 8:00 and 10:00 pm) which was attributed to non-wear during overnight hours as participants were instructed to remove the monitor while sleeping.

Descriptive statistics

On average, participants reported moderate levels of intentions to engage in PA (*M* = 3.08, *SD* = 1.32 on a 1 to 5 scale) when prompted through EMA. Accelerometer data indicated that, on average participants engaged in less than 5 min of MVPA in the 3 h after the EMA prompt (*M* = 4.76, *SD* = 8.06, range = 0–114). Average ratings for positive and negative affect were 3.07 (*SD* = 0.98) and 1.45 (*SD* = 0.67), respectively, on a 1 to 5 scale. Average rating for feelings of energy and fatigue were 2.73 (*SD* = 1.12) and 1.90 (*SD* = 1.00), respectively, on a 1 to 5 scale. Participants reported being indoors in 78.4% of valid EMA prompts and alone in 46.8% of valid EMA prompts.

Describing short-term intention-behavior coupling

Across all occasions, participants intended to be physically active in the next few hours 41% of the time ($n_{observations}$ = 574). On occasions that participants reported short-term intentions to be physically active, participants engaged in PA (i.e., accumulated at least 10 min of MVPA as measured by accelerometer in the 3-hour window after the EMA prompt) 16% of the time ($n_{observations}$ = 90) whereas the remaining 84% of the time participants intended to be active, they did not subsequently engage in PA ($n_{observations}$ = 484). On occasions that participants did not intend to be active, participants subsequently engaged in PA 10% of the time ($n_{observations} = 78$) whereas the remaining 90% of the time participants did not intend to be active, they did not subsequently engage in PA ($n_{observations} = 728$).

Using intensive longitudinal data to predict short-term intentions to engage in physical activity

The left column of Table 1 displays results from the exploratory analysis demonstrating how ILD from EMA can be used to examine time-varying predictors of short-term intention formation. Participants were more likely to intend to be active in the mornings (OR = 2.16, $p < 0.01$), but less likely to intend to be active in the evenings (OR = 0.32, $p < 0.01$) compared to other times during the day. Participants were also more likely to intend to be active on weekend days compared to weekdays (OR = 1.69, $p < 0.01$). Odds of intending to be active were unrelated to momentary positive affect, negative affect as well as feelings of energy and fatigue at a given EMA prompt. Physical and social contexts at a given EMA prompt were unrelated to odds of intending to be active.

Predicting short-term intentions followed by physical activity

The center column of Table 1 displays results from the exploratory analysis demonstrating how ILD from EMA can be used to examine time-varying predictors of short-term intentions followed by PA (compared to short-term intentions followed by no PA). Odds of intentions followed by PA were greater on occasions when individuals reported higher levels of positive affect than was typical for them (i.e., a WS association; OR = 2.20, $p < 0.01$). Momentary levels of energy, fatigue, and negative affect were not significantly associated with the odds of intentions followed by PA. Odds of intentions followed by PA were unrelated to the physical or social contexts at a given EMA prompt. Time of day and day-of-week were unrelated to the odds of intentions followed by PA.

Predicting non-intentions followed by physical activity

The right column of Table 1 displays results from the exploratory analysis demonstrating how ILD from EMA can be used to examine time-varying predictors of short-term non-intentions followed by PA (compared to short-term non-intentions followed by no PA). Non-intentions followed by PA was less likely to occur during the evening compared to other times during the day (OR = 0.14, $p < 0.05$). Affective state variables were unrelated to the odds of non-intentions followed by PA as were the social and physical contexts at a given EMA prompt. Day of week was unrelated to the odds of non-intentions followed by PA.

Table 1 | Multilevel logistic regression results predicting intentions and intention-behavior coupling using EMA Data

Predictor variable	Intention formation[a] Estimate (CI)	Intentions followed by physical activity[b] Estimate (CI)	Non-intentions followed by physical activity[c] Estimate (CI)
Affect			
Model 1			
BS positive mood	3.09** (1.43, 6.67)	0.79 (0.41, 1.51)	1.44 (0.32, 6.45)
WS positive mood	0.92 (0.66, 1.29)	2.20** (1.29, 3.76)	0.49 (0.20, 1.23)
Model 2			
BS negative mood	0.82 (0.30, 2.22)	1.46 (0.44, 4.80)	0.73 (0.12, 4.28)
WS negative mood	1.64 (0.90, 2.98)	0.28† (0.07, 1.13)	3.58† (0.96, 13.46)
Model 3			
BS energy	3.76** (1.87, 7.56)	0.77 (0.39, 1.51)	5.59† (0.97, 32.29)
WS energy	1.23 (0.91, 1.65)	1.59† (0.98, 2.61)	1.09 (0.37, 3.22)
Model 4			
BS fatigue	0.57 (0.26, 1.26)	0.57 (0.26, 1.24)	3.14 (0.44, 22.56)
WS fatigue	0.87 (0.63, 1.20)	0.88 (0.67, 1.16)	1.11 (0.44, 2.81)
Physical context			
Model 5			
BS indoors	0.80 (0.03, 23.96)	0.50 (0.06, 4.20)	0.10 (0.01, 15.31)
WS indoors	0.43 (0.15, 1.21)	0.47† (0.23, 1.12)	0.48 (0.36, 6.51)
Social context			
Model 6			
BS alone	0.26 (0.04, 1.72)	5.70 (0.54, 59.85)	7.61* (1.35, 42.49)
WS alone	0.81 (0.46, 1.41)	1.72 (0.58, 4.36)	0.83 (0.15, 4.64)
Temporal processes			
Model 7			
Morning	2.16** (1.45, 3.21)	1.32 (0.67, 2.58)	1.45 (0.57, 3.68)
Model 8			
Afternoon	0.90 (0.62, 1.31)	0.83 (0.42, 1.62)	1.93 (0.76, 4.90)
Model 9			
Evening	0.32** (0.19, 0.55)	0.82 (0.27, 2.41)	0.14* (0.03, 0.76)
Model 10			
Weekend	1.69** (1.14, 2.44)	0.87 (0.45, 1.71)	0.44 (0.17, 1.18)

Note: [a] Not forming intentions served as the reference group. [b] Intentions followed by no physical activity served as the reference group. [c] Non-intentions followed by physical activity served as the reference group. Separate multilevel logistic regression models are run for each variable (variables disaggregated into Between-Subject [BS] and Within-Subject [WS] predictors are included in the same model). Therefore, the WS results can be interpreted as adjusted for BS effects. In total, 10 multilevel logistic regressions were run predicting each outcome. Each model is adjusted for participant's BMI, gender, and income. ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

DISCUSSION

This paper described novel methods by which ILD from EMA and accelerometry can be used to investigate short-term intention-behavior coupling. This study is the first to take an EMA approach to describe the extent to which intentions and PA behavior are coupled over the short-term among healthy, low-active adults. Although previous research has investigated the formation and enactment of PA intentions, prior work has primarily focused on factors predicting intention formation and intention-behavior coupling over longer periods of time up to several months. The current study extends this work by demonstrating the utility of ILD to focus on momentary-level mechanisms underlying short-term intention-behavior coupling. Taken as a whole, understanding intention-behavior coupling from both long- and short-term perspectives could serve well to understand planned behavior and more spontaneous motivated action.

The findings from this empirical case study suggest a larger intention-behavior gap when assessing short-term intentions and behavior (i.e., 84%) than the gap documented in previous research examining long-term intention-behavior coupling. In the meta-analysis by Rhodes and de Bruijn [7], which examined intention-behavior coupling in people over longer time scales (e.g., weeks, months), results indicated that the overall intention-behavior gap was approximately 46%. Additionally, in the present study, the odds of engaging in intended versus unintended PA were approximately equal (both occurred in 6% of all occasions). This finding may suggest the limited role of short-term intentions in predicting subsequent PA behavior over time periods up to a few hours and perhaps points to the need to refine health behavior theories and explore other time-varying constructs such as contextual factors (e.g., affective state, physical and social contexts) as an influential driver of momentary decisions to engage in PA across the day.

The measurement of PA through accelerometers likely contributed to differences in the prevalence of intention-behavior coupling events in the present study compared to the person-level intention-behavior coupling profiles noted in previous research [7]. This is the first study to examine intention-behavior coupling using an objective measure of PA. Objectively assessing PA provides a strict criterion for defining whether or not a person engaged in PA (i.e., at least 10 min of MVPA within 3 h of the EMA prompt). Intention may be more sensitive to a subset of volitional behavior that is salient to an act. Accelerometers may capture both salient (e.g., walking for health) and less purposeful (e.g., fast walking to catch the bus, walking while shopping) movement that does not fall under originally intended behavior. This suggests that the momentary intention-behavior gap regarding purposeful, volitional PA may be even higher than was documented in this study.

Results from this empirical case study application suggest that time-varying factors, which are not amenable to long-term behavioral forecasting of intention-behavior relations because of their temporal nature, such affective state, time of day, and day of week may be useful for predicting either intention formation or short-term intention-behavior coupling. For example, participants were more likely to intend to be active in the mornings but less likely to intend to be active in the evenings. Furthermore, participants were less likely to engage in unintended PA in the evenings compared to other times of the day. These findings are consistent with research on the self-regulation of behavior, which suggests that self-regulation occurs on an ongoing basis and as individual progresses 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 [24]. Therefore, individuals may be less likely to intend to engage in PA and less likely to subsequently engage in PA in the evenings [25]. Research on unhealthy snacking also supports this phenomenon, with individuals who intend to limit unhealthy snacking reporting consuming fewer unhealthy snacks earlier in the day (unhealthy snacks between 11:00 am and 2:00 pm, and 5:00 pm and 8:00 pm) compared unhealthy snack consumption later in the day (between 8:00 and 11:00 pm) [26].

Findings from this exploratory analysis also revealed that on occasions when positive affect was higher than usual for a given person, that person was more likely to follow through with intentions to engage in PA. Affect has been previously hypothesized as a driver of PA action control [5] but this is the first study to examine affect rather than affective attitudes at the between- and within-person level. On occasions when individuals experience higher levels of positive affect than is typical for them, they may anticipate upcoming PA to be more enjoyable or pleasurable and consequently be more likely to engage in intended PA [5]. A recent review on acute (e.g., within a few hours) relationships between affective and physical feeling states and PA concluded that positive affective states were positively associated with subsequent PA over the next few hours whereas associations between negative affect states and subsequent PA were equivocal [27]. Although, this review did not address the issues of affective states and intention-behavior coupling specifically, it does support findings that higher than usual levels of positive affect were associated with greater odds of engaging in PA.

Within this empirical case study application, physical and social contexts were unrelated to intention formation as well as intention-behavior coupling. Previous EMA studies have found that adults are more likely to engage in PA on occasions when they are outdoors and adults are more likely to engage in PA on occasions when they are alone [27]; however, these factors did not seem to be associated with intention formation or intention-behavior coupling. Being outdoors may prompt PA of low intensity such as standing or slow walking that did not correspond with this study's definition of PA in the intention item, nor correspond with accelerometer defined cut points of MVPA. This may explain the discrepancy between findings from this study and previous work regarding the context in which PA occurs. Future iterations of this type of work should continue to investigate the role of the physical and social contexts to develop a clear understanding of the role of context (or lack thereof) in intention-behavior relations.

It is important to note that the time-varying predictors tested as part of this empirical case study application are not all encompassing of the possible predictors of intention formation or short-term intention-behavior coupling. Characteristics of the built environment such as safety or access to parks, as well as action or coping planning and other self-regulatory processes among others would be useful to explore in future iterations of work investigating short-term intention-behavior coupling. As technology continues to advance and opportunities to collect ILD on health behaviors in the context of everyday life increase, this rich data can be used to explore a variety of time-varying predictors that can help to explain the nuances of short-term intention-behavior coupling.

Study limitations and future methodological directions

In this empirical application, nearly 40% of observations eliminated due to accelerometer non-wear (n = 643) occurred during the period following either the first (i.e., at 6:30 am) or last prompt (i.e., between 8:00 and 10:00 pm) of the day, which was attributed to non-wear during overnight hours because participants were instructed to remove the activity monitor while sleeping. Exercise occasions occurring within 2 hours after the last EMA prompt of the day, but within an hour before bedtime, could be excluded because the 3-hour window in which they occurred was classified as non-wear according to the criteria used. Thus, it is possible that this study underestimated engagement in physical activity at the end of the day at the prompt occurring between 8:00 and 10:00 pm. Unfortunately, missing data is a common characteristic of ILD [28] (for more discussion of missing EMA data in Project MOBILE, see [29]). Additionally, established guidelines have not been developed regarding the amount of wear-time needed to consider a within-day, momentary period valid. Future studies collecting ILD through EMA could tailor EMA protocols to align with individuals' daily sleep and wake time to reduce the possibility of missing data. Such tailoring would likely require a custom EMA application as a number of commercially available experience sampling methods for EMA do not currently offer such features.

Additionally, missing data could further be addressed by incorporating mobile and wearable sensor technologies to passively collect behavioral or contextual data that may be particularly relevant to intention-behavior coupling. In additional to accelerometers that were employed in this study, dosimeters that capture ultraviolet exposure from the sun, personal air pollution monitors, and global position systems to track geolocation can all provide potentially valuable contextual information that could provide insights in to intention-behavior concordance or discordance. These types of passive data collection are less reliant on participant's ability to complete questionnaires regarding the features of their current context and can thus provide more complete data. Wearable and sensor data may also be relevant for intention-behavior coupling of other health behaviors such as sedentary behavior, smoking, and eating behaviors.

While this study is novel in that it is the first to study predictors of intention-behavior coupling via and objective measure of PA, waist-worn accelerometers are unable to accurately detect activities like bicycling (due to the position on the waist) or swimming (due to the monitor's inability to get wet). Although national panel data from the American Time Use Study and National Health and Nutrition Examination Survey suggest that US adults rarely engage in bicycling or swimming (less than 1% of adults report engaging in either of these activities on a given day) [30] and data from this study support these statistics (self-reported engagement in PA via EMA prompt indicated that bicycling or any other types of PA including swimming was selected in only 2% of EMA prompts). Therefore, it is unlikely that participation in PA not captured by the accelerometer, such as bicycling or swimming, biased the results of this study. Researchers interested in using an objective measure of PA to study intention-behavior coupling should consider the type or domain of PA referenced in the assessment of intentions as well as the common and likely types of PA their sample of interest will engage in and select or create the most appropriate measure given those specifications.

Additionally, this empirical application relied on single-item or extremely brief measures in EMA questionnaires, which may have narrowed the representativeness of the assessments used. It is possible that using these measures biased or attenuated actual associations documented in this study. Although using single-item or brief measures of constructs is standard practice in EMA studies because of the need to consider participant fatigue and burden, future work should focus on validating these types of measures. Furthermore, to avoid fatiguing and burdening participants, many EMA items only appeared in a portion of EMA prompts. This strategy limited the total number of items participants completed at a given prompt to 19 items and the approximate amount of time to complete an EMA survey to 3 minutes. Because participants were being prompted eight times per day, it was important to keep each EMA prompt relatively brief and the percentages for each construct were prioritized based on the primary aims of Project MOBILE and the potential for novel contributions of findings. Researchers employing EMA should consider the number of constructs to be assessed in each prompt, the number of items assessing each construct, and the number of prompts per day as well as pilot testing of an EMA protocol to determine the potential burden and fatigue experienced by participants.

This study was not powered to adequately detect time-invariant factors that influence short-term intention-behavior coupling as evidence by the large confidence intervals for many between-person effects in Table 1. However, these variables served as control variables as it is necessary to it disaggregate time-varying predictor variables into within-person and between-person effects [23]. Investigating the role of relatively stable, person-level factors such as PA habit strength or self-identity may be particularly useful in explaining short-term intention formation and enactment given the role of these factors in more long-term intention-behavior coupling [5, 6].

Finally, while this sample was fairly diverse with respect to race and ethnicity, the sample was fairly homogeneous with respect to sex and physical activity levels. Future research should explore intention-behavior coupling in men as well as in individuals who meet physical activity guidelines. Due to the rarity of participants engaging in MVPA in the 3 hours after the prompt (<2% of EMA prompts), this study was unable to consider discrete 10-min bouts of MVPA; rather it used 10 min of MVPA accumulated over the 3 hours. Results may differ for 10-min bouts of MVPA following short-term intentions to engage in PA.

Future applications

Novel approaches, such as the one employed in this paper, to understand the complex relations between psychological, affective, and contextual factors and health behaviors can form the basis of Just-In-Time Adaptive Interventions (JITAIs) [31]. JITAIs use real-time data (collected passively or actively) to inform when, where, and how interventions (i.e., recommendations, information, nudges) should be delivered in order to have optimal impact [32]. The findings from this empirical application point to novel, contextual factors that can hinder or facilitate intention formation and enactment. The accumulation of these types of findings has enormous potential to facilitate behavior change within the context of everyday life through JITAIs. This work also points to the need to examine time-varying reciprocal relationships between motivation and behavior through dynamical system 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 in the context of everyday life [33].

SUMMARY AND CONCLUSION

The overall objective of this paper was to describe methods for using ILD to investigate short-term intention-behavior coupling. Results from this empirical application are the first of its kind to indicate the possibility of both time-invariant and time-varying factors predicting the formation and enactment of short-term PA intentions across the day. Understanding the role that these processes play in intention formation as well as intention-behavior coupling is necessary to determine the processes that regulate PA in the context of everyday life and ultimately develop more effective, tailored interventions for individual behavior change.

Compliance with ethical standards

This work has been submitted solely to TBM and has not been previously published, either in part or in whole, and the findings have not been posted online. The corresponding author has had access to all aspects of the research and writing process and assumes complete responsibility for the paper. All authors have control of the primary data and agree to allow the journal to review the data if requested. All authors agree with the form and content of the submitted manuscript and the ordering of the authorship. All procedures performed in studies involving human participants were in accordance with the ethical standards of the University of Southern California and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all individual participants included in the study.

Conflict of interest

The authors declare that there are no conflicts of interest.

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