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REGULAR ARTICLE

Continuous-Time Modeling of the Bidirectional Relationship Between Incidental Affect and Physical Activity

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Abstract

Background Previous research suggests that there is a bidirectional relationship between incidental affect (i.e., how people feel in day-to-day life) and physical activity behavior. However, many inconsistencies exist in the body of work due to the lag interval between affect and physical activity measurements.

Purpose Using a novel continuous-time analysis paradigm, we examined the temporal specificity underlying the dynamic relationship between positive and negative incidental affective states and moderate-to-vigorous physical activity (MVPA).

Methods A community sample of adults (n = 126, M_{age} = 27.71, 51.6% Male) completed a 14-day ambulatory assessment protocol measuring momentary positive and negative incidental affect six times a day while wearing a physical activity monitor (Fitbit). Hierarchical Bayesian continuous-time structural equation modeling was used to elucidate the underlying dynamics of the relationship between incidental affective states and MVPA.

Results Based on the continuous-time cross-effects, positive and negative incidental affect predicted subsequent MVPA. Furthermore, engaging in MVPA predicted subsequent positive and negative incidental affect. Incidental affective states had a greater relative influence on predicting subsequent MVPA compared to the reciprocal relationship. Analysis of the discrete-time coefficients suggests that cross-lagged effects increase as the time interval between measurements increase, peaking at about 8 h between measurement occasions before beginning to dissipate.

Conclusions The results provide support for a recursive relationship between incidental affective states and MVPA, which is particularly strong at 7–9 hr time intervals. Future research designs should consider these medium-term dynamics, for both theory development and intervention.

Keywords Continuous-time · Dynamic · Incidental affect · Physical activity

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Introduction

The physiological and psychological health benefits associated with moderate-to-vigorous intensity physical activity are extensive [1–3]. While most adults perceive physical activity to be essential for their health [4], globally, the proportion of individuals who fail to meet international guidelines for physical activity is high and is rising in high-income countries [5]. In response to the low to moderate predictive power of rational/cognitive approaches to changing physical activity behavior, recent theoretical and intervention efforts have focused on affective factors that might bolster health-enhancing behavior, generally, and physical activity, in particular [6].

In line with contemporary definitions of affect [7], in the behavioral medicine domain, *affect* is defined as: "an evaluative neurobiological state that manifests in: (1) coordinated patterns of physiological (e.g., release of hormones, increased heart rate) and involuntary behavioral (e.g., facial expression, vocalization) changes, and (2) subjective experiential feelings (e.g., the phenomenal experience of pleasure, anger, embarrassment, etc.)" [8] [(p1268)]. Moreover, affect is dynamic, constantly varying in response to internal (i.e., interoceptive) and external (i.e., contextual) stimuli [9]. To date, a multitude of theories have been used to explain how affect, and affect-related constructs, influence physical activity behavior [6]. A recent conceptual framework that considers the full breadth of affective factors implicated in physical activity behavior change corresponds to the integrative framework proposed by Williams, Rhodes, and Conner [8]. As part of this integrative framework, Williams and colleagues emphasized the importance of distinguishing between *integral* and *incidental affect* [8, 10].

Integral affect refers to one's affective response during or immediately following a given behavior (e.g., how one feels *while* being physically active) that is experienced in the context of that behavior [8, 10, 11]. In contrast, *incidental affect* is the affect one feels in day-to-day life that is not experienced in the context of the behavior under investigation (e.g., physical activity) but may influence or be influenced by that behavior [8, 10, 11]. Specifically, Williams and colleagues note that affect is "pervasive and ongoing and thus, outside the context of the target behavior, [affect] exists as incidental affect both before and following the target behavior" [8] [(p1273)]. On the basis that individuals spend most of their time not engaging in moderate-to-vigorous physical activity (i.e., 99% of their time) [12], it is imperative to examine the affective states experienced in daily life that predict subsequent physical activity, as well as the longer-term, diffuse effects that engaging in physical activity has on subsequent affective states (i.e., incidental affect).

Within the physical activity domain, evidence suggests that incidental affect is both an antecedent and outcome of physical activity behavior [13–18]. Specifically, several studies have found that individuals who experience higher levels of positive incidental affect (or less negative incidental affect) are more likely to be physically active [13–15, 19, 20]. Evidence also suggests that many individuals also experience increased positive and decreased negative incidental affect following a bout of physical activity [13, 15, 20]. Moreover, these effects have been observed regardless of whether positive and negative affect were operationalized as opposite ends of a single bipolar dimension, or two separate unipolar dimensions [13, 19–22].

Recent health behavior theories have proposed recursive feedback loops between affective constructs and physical activity [23]. For example, the *broaden-and-build loop* in the *upward spiral theory of lifestyle change* describes how more positive (and less negative) affective states facilitate engagement in health-enhancing behaviors, which in turn feedback to bolster future affective states; thus, promoting health behavior change [23]. Specifically, as an antecedent, it is theorized that more positive (and less negative) incidental affect allows people to expand their resources, thus encouraging approach behaviors, such as physical activity. In turn, engagement in physical activity is theorized to be associated with several acute biological (e.g., release of neurotransmitters), psychosocial (e.g., self-efficacy, social support), and behavioral (e.g., improved sleep) adaptations to further bolster affective processes [24–26].

However, despite empirical evidence and theoretical postulates regarding the reciprocal relationships between incidental affect and physical activity, studies on the relationships between these two constructs typically focus on one direction or the other, without directly testing the potential dynamic and reciprocal interplay between the two constructs *simultaneously* [14, 16–18]. For example, in a review by Liao and colleagues [15], the purported "bidirectional" relationships highlighted between incidental affect and physical activity behavior were based on separate studies or separate analyses within the same study. These unidirectional analytic models cannot adequately test the potential recursive, affective processes underlying physical activity behavior. Additionally, by modeling these effects separately, researchers cannot ascertain the relative influence of each variable on each other [13, 27]. Knowing the relative influence of these effects can be instrumental in identifying which variable is driving dynamic relationships between constructs to identify, for example, a relatively better target for intervention [27].

To address this limitation, a recent study simultaneously examined within-day reciprocal relationships between structured exercise and incidental affect across six months among a sample of low-active, overweight/obese adults [13]. Emerson and colleagues [13] observed that a one standard deviation unit increase in incidental affect earlier in the day was associated with a 79% increase in the odds that an individual would engage in a structured walking-for-exercise session (as assessed by a binary measure) at some point later the same day. Furthermore, individuals rated their incidental affect later in the day as being more positive on days when they were physically active compared to days when they were not. Moreover, by simultaneously modeling this reciprocal relationship, the authors concluded that the influence of incidental affect on whether a participant was engaged in structured exercise was twice that of the effects of exercise on later incidental affect [13].

Although additional evidence has supported this dynamic relationship, there have been inconsistencies in the methods, analyses, and findings across studies. For example, in a study looking at acute effects of incidental affect on physical activity, feeling acutely more positive, less negative, and less tired than one's usual levels were associated with more minutes of objectively measured physical activity in a subsequent 15-min window; however, these associations were not found when a subsequent thirty minute window was sampled [14]. Furthermore, spending more minutes in physical activity than one's usual level was not associated with changes in subsequent positive or negative affect [14]. Similarly, a recent study demonstrated that increases in affective arousal were associated with greater engagement in physical activity over the following 120 min [18]. However, affective arousal did not significantly predict subsequent physical activity for the 5- or 60-minute intervals. Moreover, changes in affective valence were not related to changes in physical activity behavior at any interval and no significant effects were observed for physical activity predicting subsequent affective valence or arousal.

Similar inconsistencies were also found in the review by Liao and colleagues [15]. Of the six studies that examined the association between positive affect and subsequent physical activity, three studies found a significant positive relationship, two found no relationship, and one found a significant negative association. Within the same review, of the eleven studies that examined the association between physical activity and subsequent positive affect, eight of these studies found a significant, positive relationship, and three did not find a significant relationship. Although the examples above correspond to the bidirectional associations between physical activity and positive affect, it should also be noted that inconsistencies were even greater in the literature when examining the association between physical activity and negative affect [15].

One factor that may explain the inconsistencies in these findings is the time interval between the incidental affect and physical activity measurements (i.e., lead-lag time). In the studies described above, the length of time between when incidental affect and physical activity were assessed varied from 15 min to 24 h between assessments [13–15, 18]. In modeling methods commonly used to examine the lagged relationships between variables (such as the cross-lagged panel model or other "discrete-time models"), the interpretation of an effect can only be generalized to the specific lag examined, thus making comparisons of effects across different studies that used different measurement intervals inappropriate [28, 29]. Differences in effects between studies may be due to differences in lag rather than actual differences in the dynamic psychological process of interest [29, 30].

This lag problem becomes further complicated in studies using ambulatory assessment designs, as incidental affect and physical activity measurements are often taken at unequal intervals [31, 32]. For example, to avoid participant reactivity (i.e., when participants change their natural behavior in anticipation of a prompt), a commonly used ambulatory assessment method is known as a signal-contingent design where participants are "pinged" (i.e., prompted to provide a response in situ) at random, or within a pseudorandom interval (e.g., a participant will receive a random "ping" within a 4 hr block) [33]. Accordingly, based on the (pseudo)random nature of the prompts, the time intervals will be unequal both within- and between-participants. Although these unequal time intervals are beneficial from a study design perspective, the resultant unequal time intervals within and between participants violate the equal sampling interval assumptions of most dynamic discrete-time modeling frameworks.

To address modeling challenges associated with these unequal sampling intervals, a common approach is for researchers to aggregate responses to create an average level of affect or physical activity observed over a particular time frame. For example, in the study described earlier by Emerson et al. [13], that examined the bidirectional relationships between physical activity and incidental affect, incidental affect was assessed multiple times a day at pseudorandom times (i.e., participants were prompted to respond to a survey at a random time within a predetermined three-hour block) during waking hours. However, within the analysis, physical activity was operationalized as a binary indicator (whether a participant exercised that day or not), and the average incidental affect scores reported before/following each physical activity bout was compared to the average incidental affect scores before/following the same time of day on a nonexercise day. Accordingly, although nuanced information was collected regarding incidental affect and physical activity behavior, the treatment of the data resulted in a loss of richness of the temporal specificity underlying these dynamic relationships.

Accordingly, there is a pressing need to examine how the bidirectional relationship between physical activity and incidental affect dynamically changes over time, as a function of the time interval under consideration. In addition to addressing the methodological shortcomings of previous research examining this bidirectional relationship (e.g., aggregating affect at a day level, assessing physical activity as a binary outcome, not accounting for unequal intervals), there are also theoretical and applied advantages to elucidating the temporal specificity of this relationship. From a theoretical perspective, it has been argued that theories in health psychology need to explicitly incorporate temporal theoretical postulates with regard to the definition of constructs, the relationships between constructs, and the explanation for these relationships [34]. With regard to previous research, each result of the lagged relationships between affect and physical activity may accurately portray the effect of incidental affect on physical activity (or vice versa) for a specific time interval. However, considering these intervals separately only represents a "snapshot" of the dynamic psychological processes of interest [32]. Instead, by exploring how the dynamic relationships between incidental affect and physical activity evolve and vary as a function of the time interval, we can better derive a complete picture of the dynamic system under study [27, 32]. Empirical evidence regarding the temporal specificity of these processes can, in turn, be used to inform future theoretical postulates, which can help to facilitate an iterative process of theory construction that explicitly accounts for temporal considerations [35].

From an applied perspective, researchers spend a considerable about of time and resources designing behavior change interventions. However, a wrongly chosen time interval might result in a null effect of the intervention, despite the fact that the intervention may have effectively changed the desired outcome during other time intervals [34]. Furthermore, if it is known, when physical activity has an optimal effect of increasing positive incidental affect, this information can be leveraged by prompting individuals to raise awareness of these "feel-better effects" at the optimal time interval [11].

Purpose

The current study aims to test the continuous bidirectional relationships between device-assessed moderate-to-vigorous physical activity (MVPA) and incidental affect and to explore the temporal specificity underlying the bidirectional relationship between incidental affect and MVPA. Specifically, in line with previous literature [13, 15] and theory [8, 23], it is hypothesized that (1) having more positive incidental affective states and less negative incidental affective states will be associated with more subsequent minutes spent in MVPA, and (2) more minutes spent in MVPA would be associated with more subsequent positive incidental affective states and less negative incidental affective states. Exploratory questions regarding the temporal specificity of this dynamic process include: (1) how long after the measurement of incidental affect is there the largest effect for predicting subsequent MVPA, (2) how long after a bout of MVPA is there an optimal effect of boosting individuals' incidental affect, and (3) how long are the theorized positive effects on incidental affect maintained after a bout of MVPA?

Methods

The study used data derived from the Ambulatory Assessment of Personality, Ecological Context, and Stress Study (AAPECS; https://osf.io/m3p4v/). Overall, the AAPECS project used ambulatory assessment techniques (e.g., smartphone administered surveys, wearable technology) to study the daily dynamic processes of stress and responses to that stress, and how levels of personality and psychopathology amplify or dampen those processes. The AAPECS dataset contains data from 311 individuals (aged 18–40 years; 53% female). Informed consent was obtained from all individual participants included in the study. Participants were recruited between 2016 and 2018, both online and through posted flyers posted throughout Pittsburgh, Pennsylvania, for a study of personality, daily stress, and social interactions. Due to the smartwatch being added later in the AAPECS study protocol only the final n = 176 (59%) participants who were registered in the study were invited to wear a smartwatch that assessed ambulatory psychophysiology (e.g., heart rate, sleep, activity levels) for 14 days. Due to technological difficulties, smartwatch data were only available from 126 participants. Only the methods pertinent to the present study are discussed. Ethical approval for the AAPECS study procedures was granted by the University of Pittsburgh. Further approval was obtained by the University of British Columbia's Behavioral Research Ethics Board. The present study was pre-registered through OSF (https://doi.org/10.17605/OSF.IO/FXJWZ) prior to receiving the data from the data custodian (BMS).

Participants

All participants were between the ages of 18 and 40 and were not currently receiving treatment for psychosis or a psychotic disorder. Preliminary screening was used to recruit a (roughly) gender-balanced sample and to ensure adequate representation of a range of personality pathology and interpersonal problems. The sample was also selected to balance individuals who had received recent mental health treatment (within the past year) with those who had not. Individuals were pre-screened using items from the Inventory of Interpersonal Problems – Personality Disorder Scales [36] and were recruited in an approximately 1-1-1 representation of low, moderate, and high levels of interpersonal difficulties within gender, treatment status, and the overall sample.

From the larger community sample (n = 311), 4.5% of participants (n = 14) were excluded for failing to complete a minimum of 10 randomly prompted surveys during the ambulatory assessment protocol resulting in a final n of 297. The present study concerns a subsample of 126 individuals for whom detailed MVPA data were available using the Fitbit Blaze. Participants in the subsample ranged in age from 18 to 40 (M = 27.41, SD = 6.51) and the subsample was 48.4% female. Most participants identified as White (77.0%), 12.7% identified as Black or African American, 7.9% as Asian, and 4.8% as multiracial or "Other." Two individuals did not indicate their racial identity. 59.7% (n = 75) of the sample had a lifetime history of mental health treatment, 62.7% (n = 47) of which were currently receiving treatment at baseline. All other demographic information is presented in the Electronic Supplementary Material 1.

Procedure

Participation in the AAPECS study was comprised of two phases—a lab session and an ambulatory assessment and passive sensing protocol. Participants first completed a baseline laboratory session, which consisted of an interview conducted by trained clinicians and a battery of self-report questionnaires. At the end of this three- to five-hour session, participants received instruction from a research assistant regarding the ambulatory assessment procedures and the smartwatch device (Fitbit Blaze). Ambulatory assessments began the day after the baseline assessment. The length of the assessment period was 14 days. The ambulatory assessment prompts were delivered six times per day during an approximately 12-hour time window corresponding to the participants' typical waking hours using MetricWire [37]. As the ambulatory assessment schedule was tailored to each participant prompts could be delivered at any hour of the day (see Electronic Supplementary Material 2 for a breakdown of the frequency of observations by hour). Blocked random intervals were set so that a minimum of 90 min passed between surveys, and participants were given 20 min to initiate a response to each one.

Participants were provided with Fitbit Blaze smartwatches during the laboratory session to track various physiological measures, including heart rate, physical activity, and sleep. Additionally, participants could receive ambulatory assessment prompts on the watch, although the questionnaires had to be answered using a smartphone. Participants typically used their own Android or iOS smartphone for the ambulatory assessments upon which a laboratory member would download the study applications (i.e., MetricWire, Fitbit). Laboratory-owned Android smartphones were also available, allowing individuals without compatible devices to participate.

All participants received $50 for the baseline assessment session. Those who answered 90% or greater of the surveys during the ambulatory assessment period earned an additional $110 (14-day ambulatory assessment). This amount was prorated by week for those who completed less than 90% of the surveys overall. Surveys completed in later weeks of the study were valued higher in the prorated compensation model. The final payment was contingent upon the return of the smartwatch (and, if applicable, the laboratory-owned smartphone). Additionally, for every 100 participants, a draw was conducted for an iPad Mini. Chances of winning increased with the number of surveys answered.

Measures

Moderate-to-vigorous physical activity

For this study, MVPA was operationalized as a superordinate term comprised of any body movement resulting in increased energy expenditure. Specifically, MVPA encompassed both moderate-to-vigorous daily lifestyle activities (e.g., active transportation, occupational MVPA) and structured exercise/leisure-time physical activity [3]. MVPA was assessed using a smartwatch (Fitbit Blaze). Participants were instructed to wear the watch during daily life and sleep, only taking it off to charge and when bathing or swimming. Two band sizes were available to accommodate a range of participant wrist circumferences. Height, weight, and gender information were gathered from participants and entered into the consumer web interface to calibrate the device. Although previous research has indicated that consumer wearables may overestimate the number of steps taken per day, the number of active minutes generated by Fitbit devices are comparable with the minutes of MVPA generated by accelerometers over 7 days [38]. MVPA was further operationalized as bouts of time lasting longer than 10 min collected by the smartwatch (i.e., multiple bouts of MVPA that occurred within a given day were treated separately, rather than collated on a daily or weekly level). In the most recent US physical activity guidelines [39], a bout is no longer restricted to physical activity lasting longer than 10 min. Nevertheless, MVPA bouts were operationalized in this study as lasting longer than 10 min as the Fitbit algorithm counts active minutes only if they last 10 min or longer [40].

Incidental affect

The momentary positive and negative incidental affect items used in the ambulatory assessment protocol were drawn from the Positive and Negative Affect Schedule (PANAS) [41, 42]. Although the PANAS traditionally includes 20 adjectives, in the present study, for the momentary scale, 8 adjectives were selected [43]. Positive incidental affect was represented by four items—*Happy, Confident, Content,* and *Excited.* Negative incidental affect was assessed using four items—*Ashamed, Nervous, Sad,* and *Angry*. Participants were asked questions in the following form: "How [*ADJECTIVE*] do you feel right now?"

Although the PANAS traditionally asks participants to rate each adjective on a five-point Likert scale (1—Not at All to 5—Extremely), ratings were made on a visual analog scale from 0 (Not at All) to 100 (Extremely). To ensure the affect measured in the present study was incidental affect, rather than the affect experienced while engaging in physical activity (i.e., affective response), the time of day that participants responded to the affect assessments was cross-referenced with the MVPA data. Any affect measures that co-occurred with a bout of MVPA were excluded from analyses in the present study, as such indicators reflect integral and not incidental affect. The within-person reliability of change coefficients [44] (i.e., the ability to detect systematic within-person changes over the study) for the positive and negative incidental affect scales were $R_C = 0.83$ and $R_C = 0.64$, respectively. The between-person reliability coefficients (i.e., the person-level averages of observations across the entire study) for the positive and negative incidental affect scales were $R_{KF} = 0.99$ and $R_{KF} = 0.99$, respectively. Based on recommendations by Nezlek [45], it was determined that in this study, the responses to both the positive and negative affect scales demonstrated acceptable reliability.

Data Analysis

A total of 8,335 responses to random prompts were collected over the course of the study, with an average of 66.15 (*SD* = 15.04, range 19–91) surveys completed per participant. Regarding physical activity, a total of 2,545 bouts of MVPA lasting longer than ten minutes were recorded by the smartwatches, with an average of 20.04 (*SD* = 17.26, range 0–91) bouts completed per participant. All missing data were considered missing at random. Specifically, from a continuous-time perspective, missing data are interpreted as reflecting unequal time intervals between measurements. Under the assumption of missing at random, missing data are equivalent to fewer discrete measurement occasions [46]. All of the time points of measurement were converted to represent elapsed time relative to the study's start date (i.e., midnight of the first full day participants wore the Fitbit), coded as $t = 0$. Data were standardized and grand-mean centered to facilitate model convergence [47].

To test our primary hypotheses, Bayesian hierarchical continuous-time structural equation models (CT-SEM) were fit using the ctsem package [47], which interfaces to Stan [48] in the R 4.0.5 environment [49]. Specifically, CT-SEM uses *stochastic differential equations* (i.e., computing a derivative) to compute the change in a variable (e.g., incidental affect/MVPA) across an infinitesimally short interval ($\Delta t \rightarrow 0$). We computed two bivariate process models for the present study; the first examined the relationship between positive incidental affect and MVPA and the second between negative incidental affect and MVPA.

Based on our pre-registered analyses (https://doi.org/10.17605/OSF.IO/FXJWZ), we intended to compute latent variables for positive and negative incidental affect using each individual affect item as manifest indicators. However, in line with previous limitations of CT-SEM analyses, the proposed analysis was ultimately too computationally burdensome [30] (estimated runtime was more than 2 months). Instead, the positive affect items were summed to create one positive incidental affect manifest indicator, and the negative affect items were summed to create a negative incidental affect manifest indicator [41]. As required by the *ctsem* software, the summated positive and negative manifest indicators loaded on latent positive and negative affect variables, respectively, with scores ranging from 0 to 500. A single indicator latent variable was also created for MVPA to account for measurement error. See Electronic Supplementary Material 3 for the full equations estimated.

In line with previous recommendations for Bayesian models, we used the default burn-in (50% of the chain), the default aggregation statistic (mean of the chain), and the default priors [50]. The priors were "weakly informative for typical conditions in the social sciences" [51] [(p9)]. We ran each Bayesian model (i.e., the positive and negative incidental affect models) using a NUTS (No U-Turn sampler) with four chains and 10,000 iterations per chain [52]. As a convergence statistic, we report the potential scale reduction factor $\hat{R}$ [52, 53]. As a precision statistic, we report the effective sample size [52, 53]. See Electronic Supplementary Material 4 for a description of and the complete code to run and test both models.

The auto- and cross-effects from the drift matrix are of primary interest to address the hypotheses. Auto-effects reflect the stability (or persistence) of incidental affect and MVPA over time. Cross-effects describe the reciprocal effects of one variable on the other. Based on the drift coefficients, we computed the autoregressive and cross-lagged effects for any time interval Δt, from immediately after to 48 hours later. Consistent with previous recommendations [54] the terms auto-effect and cross-effect represent the continuous-time parameters, whereas autoregressive and cross-lagged effect represent the discrete-time parameters. From the discrete-time cross-lagged effects, we also determined the time interval where the dynamic processes reached their peak effects and the discrete-time coefficients at those maximum or minimum time intervals [55]. In interpreting the model outputs, we assessed the parameter's posterior mean in relation to its posterior standard deviation (SD) and posterior 95% Bayesian credibility intervals (BCI). With 95% credibility, the BCI indicates the probability that the parameter falls between the lower (2.5%) and upper (97.5%) limits. Specifically, if zero did not fall within the upper or lower limits of the BCI of the parameter, then we concluded that the nonzero parameter estimate was not due merely to sample fluctuations, thus is relevant for interpretation.

Results

Run time and RAM usage of the Bayesian estimation needed approximately 20 GB RAM and 9 days and 3 h of runtime for the MVPA and positive incidental affect model and 10 days and 16 h for the MVPA and negative incidental affect model, on an Intel i9-10900T (4.60 GHz Turbo) CPU of a 64-bit Windows OS, with 64 GB RAM. As a check on the estimation process, all parameters had a minimum of 800 effective samples (range 866.42–20149.00 effective samples) and an $\hat{R}$ of 1.00, indicating adequate model convergence and precision. Additionally, based on the prediction model by Hecht and Zitzmann [56, 57] using N = 126, T = 19 (the minimum number of prompts completed by a participant), and standardized peak effect set to 0.05 (the smallest standardized peak effect observed), our *post hoc* analysis suggests we had a sufficient sample size to reliably estimate the continuous-time cross-lagged dynamics between affect and physical activity behavior (estimated "power" for standardized peak cross-lagged effect = 1.00). It should be noted, however, that "power" typically pertains to frequentist, not Bayesian estimation methods [58]. The posterior means, standard deviations, and 95% BCI estimates of the means of the population distributions presented in Tables 1 and 2 are represented by Figs. 1 and 2 for the positive affect and negative incidental affect models, respectively.

Descriptive Statistics

The person means for weekly minutes of MVPA ranged from 0 to 1045.50 min (M = 189.11, SD = 184.38 min). The person means for average length of MVPA bouts ranged from 10.0 to 43.5 min (M = 17.91, SD = 5.37 min). For incidental affect, the person means ranged from 32.01 to 353.27 (M = 185.61, SD = 55.29) for positive affect, 0.69–190.78 (M = 51.04, SD = 40.93) for negative affect.

Positive Incidental Affect Model

The population means for the T_0 mean parameters in Table 1 represent the relationship between the participants' initial states and subsequent states throughout the latent process [50]. A negative T_0 mean denotes that the initial state of the process was lower than future states, whereas a positive value indicates that the initial state was higher. For positive incidental affect, the results indicate that there was no substantial increase or decrease in the overall level of (the latent indicator of) positive affect

Table 1. Means, Standard Deviations, and Posterior Credibility Intervals for the Means of Estimated Population Distributions of the Bivariate Relationship Between Positive Incidental Affect and MVPA.

Dependent process	Positive affect						MVPA					
Parameter	Est.	SD	BCI [2.5%, 97.5%]		$\hat{R}$	N_{eff}	Est.	SD	BCI [2.5%, 97.5%]		$\hat{R}$	N_{eff}
T_0 Mean	−0.18	0.12	−0.41	0.05	1.00	3138.24	0.42	0.10	0.23	0.62	1.00	8185.71
Continuous-Time Intercept	0.01	0.01	−0.003	0.03	1.00	5525.37	−0.02	0.01	−0.03	−0.02	1.00	7620.70
Manifest Variance	0.51	0.01	0.49	0.51	1.00	3569.78	0.92	0.01	0.91	0.94	1.00	13033.51
Between-subject parameter												
MVPA	−0.96	0.03	−0.99	−0.89	1.00	201000	–	–	–	–	–	–
Drift parameters												
Positive Affect	−0.06	0.01	−0.08	−0.04	1.00	3669.82	0.25	0.06	0.14	0.35	1.00	2291.00
MVPA	0.02	0.01	0.01	0.04	1.00	6563.25	−0.31	0.03	−0.38	−0.24	1.00	8190.03
Diffusion parameters												
Positive Affect	0.04	0.01	0.03	0.07	1.00	2714.23	–	–	–	–	–	–
MVPA	−0.03	0.01	−0.04	−0.02	1.00	2625.62	0.04	0.01	0.02	0.06	1.00	9690.15

Note: N = 126; *Est.* = mean of the chain; *BCI* = Bayesian credibility interval; $\hat{R}$ = potential scale reduction factor; N_{eff} = effective sample size; *MVPA* = minutes of moderate-to-vigorous physical activity; between-subject parameter is the raw population correlation between the continuous-time intercepts; diffusion parameters are of the regular variance-covariance matrices.

Table 2. Means, Standard Deviations, and Posterior Credibility Intervals for the Means of Estimated Population Distributions of the Bivariate Relationship Between Negative Incidental Affect and MVPA.

Dependent process												
	Negative affect						MVPA					
Parameter	Est.	SD	CI [2.5%, 97.5%]		$\hat{R}$	N_{eff}	Est.	SD	CI [2.5%,97.5%]		$\hat{R}$	N_{eff}
T_0 Mean	0.22	0.10	0.02	0.42	1.00	1462.49	0.40	0.10	0.21	0.60	1.00	9769.51
Continuous-Time Intercepts	−0.01	0.006	−0.02	0.002	1.00	3346.25	-0.02	0.01	−0.03	−0.001	1.00	8114.44
Manifest Variance	0.52	0.01	0.50	0.54	1.00	1742.62	0.92	0.01	0.91	0.94	1.00	12313.07
Between-subject parameters												
MVPA	0.92	0.09	0.66	0.98	1.00	19327	–	–	–	–	–	–
Drift parameters												
Negative Affect	−0.04	0.01	−0.06	−0.03	1.00	1995.94	−0.30	0.04	−0.39	−0.23	1.00	7925.38
MVPA	−0.02	0.01	−0.04	−0.002	1.00	3824.27	−0.19	0.06	−0.30	−0.06	1.00	921.59
Diffusion parameters												
Negative Affect	0.03	0.01	0.02	0.06	1.00	1150.47	–	–	–	–	–	–
MVPA	0.03	0.01	0.01	0.04	1.00	866.42	0.04	0.01	0.02	0.06	1.00	8699.31

Note: N = 126; *Est*. = mean of the chain; *BCI* = Bayesian credibility interval; $\hat{R}$ = potential scale reduction factor; N_{eff} = effective sample size; *MVPA* = minutes of moderate-to-vigorous physical activity; between-subject parameter is the raw population correlation between the continuous time intercepts; diffusion parameters are of the regular variance-covariance matrices.

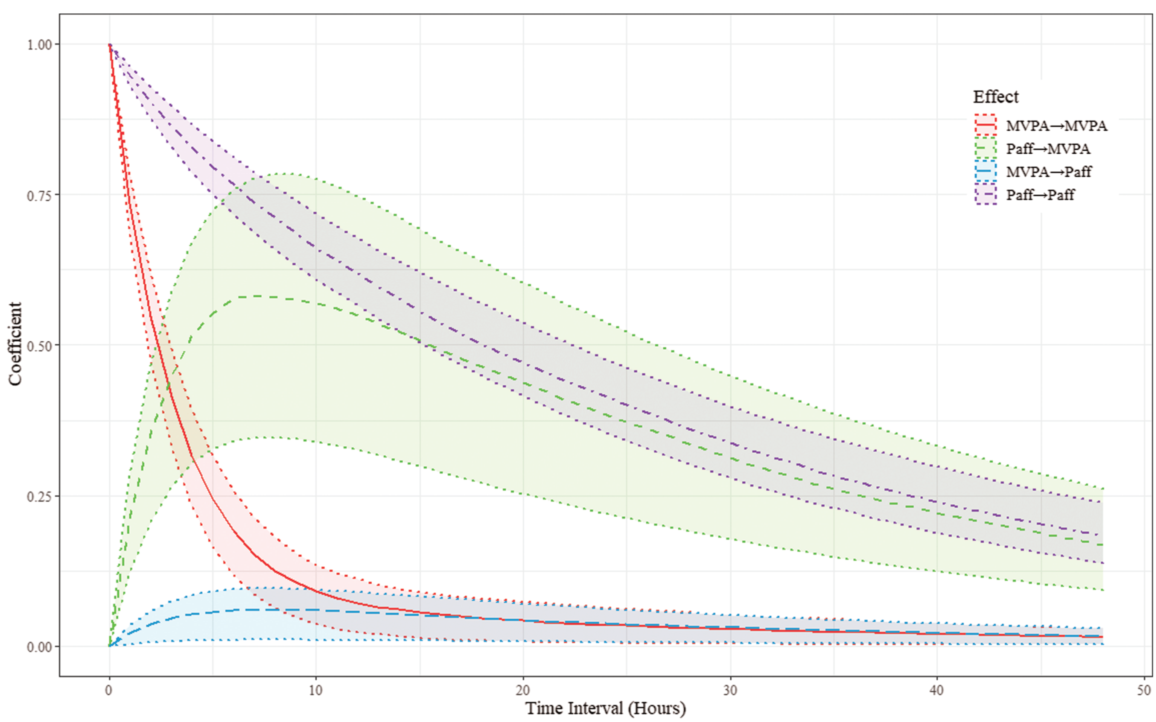

Fig. 1. Posterior mean and 95% credibility intervals for the standardized discrete-time autoregressive effects (i.e., persistence of MVPA (indicated by the solid, red line) and positive incidental affect (PA; indicated by the dot-dashed, purple line) and the cross-lagged effects (i.e., association between MVPA and positive affect at the subsequent time point (indicated by the long-dashed, blue line), and between positive incidental affect and MVPA at the subsequent time point (indicated by the short-dashed, green line)) at time interval lengths up to 48 hours. Please see the online version for the color version of the figure.

over time, with the 95% BCI encompassing 0 ($M = -0.18$, $SD = 0.12$, 95% BCI [−0.41,0.05]). In contrast, for MVPA, the results for the mean T_0 were positive, indicating that participants` MVPA levels decreased throughout the study ($M = 0.43$, $SD = 0.10$, 95% BCI [0.23, 0.62]). The continuous-time intercepts represent the average process

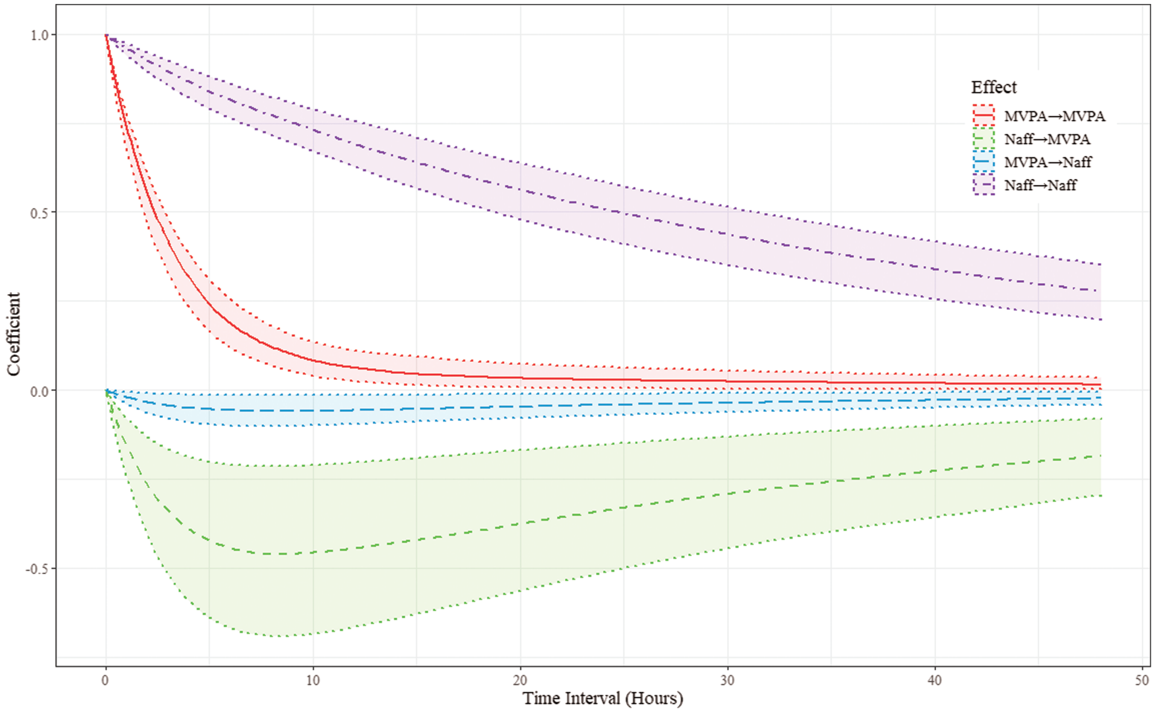

Figure 2. Posterior mean and 95% credibility intervals for the standardized discrete-time autoregressive effects (i.e., persistence of MVPA (indicated by the solid, red line) and negative incidental affect (NA; indicated by the dot-dashed, purple line) and the cross-lagged effects (i.e., association between MVPA and negative affect at the subsequent time point (indicated by the long-dashed, blue line), and between negative affect and MVPA at the subsequent time point (indicated by the short-dashed, green line)) at time interval lengths up to 48 hours. Please see online version for the color version of the figure.

means for positive incidental affect and MVPA, thus are not of substantive interest for the present study (because they were grand-mean centered and standardized in data processing). The manifest variance was relatively larger for MVPA than positive incidental affect, which points to larger observed within-person variability for MVPA.

The drift parameters in Table 1 are of particular interest in this study. The drift parameters reflect the direct instantaneous ($\Delta t \rightarrow 0$) temporal relationships between MVPA and incidental affective states [59]. The parameters of positive incidental affect on subsequent positive incidental affect and MVPA on subsequent MVPA represent the auto-effects. Auto-effects are interpreted as the relationship a variable has with its own rate of change [59]. The closer the estimates are to zero, the longer the changes persisted over time. Additionally, a negative estimate reveals a diminishing auto-effect effect over time (i.e., reverting to baseline), whereas a positive estimate represents an explosive process (i.e., accelerating away from baseline over time [50]. As evidenced in Table 1 and Fig. 1, positive incidental affect ($M = -0.06$, $SD = 0.01$, 95% BCI [−0.08, −0.04]) was relatively more persistent over time, compared to MVPA ($M = -0.31$, $SD = 0.04$, 95% BCI [−0.38, −0.24]).

To assess the bidirectional dynamic relationship between incidental positive affect and MVPA over time, we first evaluated the off-diagonal drift matrix parameters representing the cross-effects in Table 1. The cross-effects represent instantaneous ($\Delta t \rightarrow 0$) temporal relationships between the two variables. A positive cross-effect indicates that an increase in the level of one process predicts an increase in the rate of change in the other process, and thus an instantaneous increase in the level of the other process [59]. As hypothesized, the results indicate that positive incidental affect predicted a subsequent increase in the minutes in which participants engaged in MVPA ($M = 0.25$, $SD = 0.06$, 95% BCI [0.14, 0.36]). Additionally, the results also support the hypothesized reciprocal relationship, such that engaging in more minutes of MVPA predicts a subsequent boost in positive incidental affect ($M = 0.02$, $SD = 0.06$, 95% BCI [0.01, 0.04]).

As the continuous-time auto-effects and cross-effects are not easily interpretable by themselves [50, 54], Fig. 1 illustrates the discrete-time effects derived from the parameters in the drift matrix. As illustrated in Fig. 1, both discrete-time autoregressive effects demonstrated an exponential decay as the time lag between measurement occasions increased [60]. From Fig. 1, it can be inferred that the discrete-time cross-lagged coefficients increase as the lag interval increased until the cross-lagged effects reached a peak at 7.21 h of lag between measurement occasions. After reaching the peak, the strength of the cross-lagged relationships begins to dissipate. With respect to MVPA predicting subsequent positive affect, the effect completely dissipated (i.e., the 95% BCI crossed 0) 45 h following a change in MVPA. In contrast, positive affect was still predictive of subsequent MVPA at lag intervals greater than 48 h.

At its peak, the cross-lagged coefficient of positive affect predicting subsequent MVPA was 0.56, meaning that a one standard deviation unit increase above an individuals' typical positive affect level resulted in a 0.56 standard deviation unit increase in their MVPA 7.21 h later, controlling for shared sources of change. While it reached its peak effect at the same time interval, the influence of MVPA on subsequent positive affect was much smaller, with the peak cross-lagged coefficient being 0.05. Moreover, positive incidental affect had a greater relative influence on predicting subsequent MVPA compared to the reciprocal relationship across all lag intervals.

The diffusion parameters in Table 1 help to further elucidate the temporal relationships between positive incidental affect and MVPA. Specifically, results from the diffusion covariance matrix of positive affect on positive affect (M = 0.04, SD = 0.01, 95% BCI [0.03, 0.07]) and MVPA on MVPA (M = 0.04, SD = 0.01, 95% BCI [0.02, 0.06]) demonstrate that each of these latent processes were influenced by random (i.e., unpredictable) fluctuations over time. The diffusion matrix covariation between the two latent processes represents the within-person correlation of random changes in these latent processes. In the present study, the relationship between positive incidental affect and MVPA provided evidence that the random changes in positive incidental affect and MVPA share some common causes (M = −0.03, SD = 0.01, 95% BCI [−0.04, −0.02]). Finally, the between-person estimate of the standardized temporal correlation between positive incidental affect and MVPA in Table 1 indicates that average levels of positive incidental affect were negatively correlated with average levels of MVPA (M = −0.96, SD = 0.03, 95% BCI [−0.99, −0.89]). That is, participants who had higher average levels of positive incidental affect tended to engage in fewer minutes of MVPA overall.

Negative Incidental Affect Model

The population means for the T_0 mean parameters for both negative incidental affect (M = 0.22, SD = 0.10, 95% BCI [0.02, 0.60]) and MVPA (M = 0.40, SD = 0.10, 95% BCI [0.21, 0.60]) suggest that levels of negative incidental affect and MVPA decreased over the course of the study among participants. Like the positive incidental affect model, the manifest variance was relatively larger for MVPA than negative incidental affect, reflecting larger observed within-person variability for MVPA.

The drift parameters are presented in Table 2 and illustrated in Fig. 2. Similar to the positive incidental affect model, the auto-effect of negative incidental affect (M = −0.04, SD = 0.01, 95% BCI [−0.06, −0.03]) was relatively more persistent over time compared to the auto-effects of MVPA (M = −0.30, SD = 0.04, 95% BCI [−0.39, −0.23]). With regard to cross-effects, consistent with our hypotheses, neither of the 95% BCI contained zero, revealing that higher levels of negative incidental affect were negatively related to subsequent minutes of MVPA (M = −0.19, SD = 0.06, 95% BCI [−0.30, −0.06]), and that more minutes of MVPA were related to lower levels of subsequent negative incidental affect (M = −0.02, SD = 0.01, 95% BCI [−0.04, −0.01]). As further illustrated in Fig. 2, the discrete-time cross-lagged effects for both latent processes decreased over time until reaching a minimum at approximately 8.64 h of lag between measurement occasions before beginning to make their way back toward zero. With respect to MVPA predicting subsequent negative affect, the effect completely dissipated (i.e., the 95% BCI crossed 0) 30 h following a change in MVPA. In contrast, negative affect was still predictive of subsequent MVPA at lag intervals greater than 48 h.

At its minimum, for a given individual a one standard deviation unit increase in the negative affect above their usual level predicted a 0.48 standard deviation unit decrease in their MVPA, 8.64 h later, controlling for shared sources of change. For the reciprocal relationship, the minimum cross-lagged parameter was much smaller (−0.05). Additionally, across all lag intervals, the influence of negative incidental affect predicting subsequent MVPA was relatively stronger than the reciprocal relationship.

Mirroring the positive incidental affect model, the diffusion variance parameters in Table 2 indicate that both negative incidental affect (M = 0.03, SD = 0.01, 95% BCI [0.02, 0.06]) and MVPA (M = 0.04, SD = 0.01, 95% BCI [0.02, 0.06]) were influenced by random fluctuations over time. There was also a within-person covariance of random changes in these latent processes, suggesting that the random changes in these two processes share common causes (M = 0.03, SD = 0.01, 95% BCI [0.01, 0.04]). Finally, the between-person parameter of temporal correlations between negative incidental affect and MVPA suggests that, on average, individuals with higher levels of negative incidental affect also had higher overall MVPA levels (M = 0.92, SD = 0.92, 95% BCI [0.65, 0.99]).

Discussion

In this study, we sought to examine the continuous bi-directional relationships between device-assessed MVPA and incidental affect. In line with our *a priori* hypotheses and previous literature [13, 15], the results indicated that having more positive incidental affective states was associated with more subsequent minutes spent in MVPA, and more minutes spent in MVPA was associated with more subsequent positive incidental affective states. Similarly, the results suggest that having more negative incidental affective states was associated with fewer subsequent minutes spent engaging in MVPA. More minutes spent in MVPA was associated with less negative subsequent incidental affective states. Accordingly, these findings support contemporary, dynamic theoretical postulates concerning feedback loops occurring between affective states and health-enhancing behaviors [23].

The majority of theorizing around the role of incidental affect in relation to health behavior change has focused on its role as a determinant of behavior, with unidirectional causal pathways [8, 10]. Instead, identifying dynamic structures, such as feedback loops, can assist in identifying processes that maintain physical (in)activity. Based on the results of this study, an individual with high levels of negative affect on a given day, tends to engage in low levels of MVPA that day, and high negative affect the following day. While the present study focused on a bivariate case of interactions between incidental affective states and MVPA, the mechanisms underlying physical activity behavior are highly complex and interconnected [61, 62]. Accordingly, future theorizing (and the analytical models used to test such theories) should continue to explicitly account for recursive, dynamic relationships where multiple affective, cognitive and behavioral factors simultaneously reinforce or suppress each other over time [61].

Also consistent with previous research [13], in the current study, the influence of positive and negative incidental affective states on subsequent MVPA was relatively more robust than the effects MVPA had on subsequent negative or positive incidental affective states. After accounting for the interconnectedness between variables, determining which direction of a reciprocal relationship is relatively stronger is instrumental for providing direction for future intervention research. Specifically, balanced against the evidence of recursive relationships between incidental affect and physical activity, the influence of incidental affective states on subsequent MVPA seems to be the driving process of the recursive relationship. Therefore, attempting to change an individual's incidental affect (i.e., increasing positive incidental affect or decreasing negative incidental affect) appears to be a particularly viable intervention target to bolster physical activity.

An additional purpose of the present study was to explore the temporal specificity of the dynamic reciprocal relationship between incidental affect and MVPA. The findings derived from this study indicate that peak cross-lagged effects for high positive incidental affect and low negative incidental affect predicting subsequent MVPA occur approximately 8 h prior to a bout of MVPA. A similar length interval was also observed in the opposite direction (i.e., MVPA predicting subsequent affect). This eight-hour lag interval is severely underrepresented in the extant literature. For example, a large proportion of studies examining the lagged effects occurring between physical activity and incidental affect use acute lag intervals (i.e., 5–120 min) [14, 18]. Another collection of studies examine the bidirectional relationships between affect and physical activity at a day level (i.e., positive incidental affect on one day predicting physical activity engagement the following day) [13, 63]. As illustrated in Figs. 1 and 2, both acute- and day-level intervals may result in underestimating the bidirectional relationships occurring between incidental affect and physical activity behavior.

From a study design perspective, this eight-hour interval appears to warrant future investigation. Furthermore, if future research provides additional support for this eight-hour interval, then, for example, this interval could be used to facilitate the development of just-in-time interventions to foster positive incidental affect (or ameliorate negative incidental affect) before a planned bout of physical activity (particularly when individuals are particularly vulnerable to diminished affective states) [11, 64].

Although not of primary interest, there are several other notable findings from the present study. In both the positive and negative incidental affect models, there was an overall trend of MVPA levels decreasing throughout the study. This finding may be an artifact of initial participant reactivity to wearing the smartwatch. With regard to future research, this finding has two key implications. First, this finding suggests the need for run-in periods in intensive longitudinal designs for participants to become familiar with the assessment methods and produce more stable assessments [65]. Second, even when using short-term, intensive longitudinal, observational designs (i.e., when MVPA or the psychological processes underling MVPA are not being intervened upon) where no systematic changes would be anticipated, we recommend researchers choose a data analysis method that can accommodate nonstationarity.

Another notable finding pertains to differences between the between-person and within-person levels of analysis [66]. In the present study, when examining the differences occurring *within an individual over time*, it was observed that when individuals experienced better affective states than their average levels, this predicted subsequent increases in their engagement in MVPA (i.e., a positive relationship). In contrast, when examining the same data from a between-person perspective, it was observed that individuals who, on average, had lower positive incidental affect and higher negative incidental affect were more physically active, *compared to other individuals* with higher average levels of positive incidental affect and lower negative incidental affect (i.e., a negative relationship). The first implication of this finding is that when researchers are interested in examining dynamic psychological processes occurring within an individual, it is imperative that the study design and selected analysis aligns with changes occurring within an individual [66, 67].

Although this negative between-person correlation contradicts the typical positive relationship observed between positive affective states and physical activity behavior [3], there are several possible explanations for why it was observed. The first rationale aligns with the "*affect regulation*" theoretical perspective of the relationship between incidental affect and physical activity behavior [11]. From an affect regulation perspective, individuals engage in behaviors that they anticipate will modify their current affective state (i.e., they report engaging in MVPA as an affect improvement strategy). As such, it is plausible that, in this sample, individuals who had lower average levels of positive incidental affect (and higher negative incidental affect) engaged in more physical activity on average to enhance their positive affect that day as a form of homeostasis. A second potential explanation corresponds to the type of MVPA participants were engaging in. In the present study, the smartwatch captured MVPA broadly and was not delimited to leisure-time physical activity or planned exercise behaviors. It has been previously demonstrated that occupational physical activity has less positive and more negative psychological effects compared to leisure-time physical activity [68]. In this sample, 55.5% of participants were employed either full-time or part-time. However, we did not collect data regarding the type of occupation. Accordingly, though speculative, it is possible that more active individuals were engaging in more occupational physical activity. Finally, it is also possible that this negative correlation is a statistical artifact that is limited only to this sample of individuals. Therefore, an important future direction is to explore if and under what conditions this negative between-person correlation holds.

Limitations

Balanced against the novel insights provided by Hierarchical Bayesian CT-SEM, there are also limitations to acknowledge. First, it is well established that hierarchical CT-SEM is very computationally intensive [30, 54]. Accordingly, CT-SEM analyses are typically limited to modeling two to three dynamic processes [30]. Within the context of the present study, though our preregistration intended to use a dynamic measurement model to account for measurement error in each individual affect item, this was infeasible as it would take months for the model to run. Instead, we summed the positive and negative affect items, and measurement error was accounted for in the summated positive and negative incidental affect manifest indicators.

A second limitation to address concerns the operationalization of incidental affect. Specifically, within their integrated framework, Williams and colleagues [8] distinguish between postbehavior affective response and incidental affect following physical activity behavior. The postbehavior affective response is positioned as a "direct result of the target behavior [11]". In contrast, postbehavior incidental affect is suggested to occur "outside the context of the target behavior (even if it is partially determined by the target behavior [13] (p131)]". Accordingly, it has been suggested that there is a need for further conceptual clarity between these two constructs to answer questions such as, "how quickly does the acute affective response to physical activity dissipate and when is affect measured postphysical activity no longer considered influenced by the target behavior (and thus no longer considered affective response)? [11] (p8)]". As illustrated in Fig. 2, MVPA has an influence on subsequent affective states greater than 30 h following a bout of physical activity. Accordingly, it still remains unclear when post-behavior affective response dissipates to become incidental affect. Thus, our post-MVPA incidental affect measure may be a blend of both integral (i.e., postbehavior affective response) and incidental affect constructs.

A final limitation pertains to how heterogeneity was accounted for through hierarchical CT-SEM. Previous research suggests that there is heterogeneity among individuals in the affective processes that underlie physical activity [69]. A strength of a hierarchical CT-SEM analysis is that population mean distributions related to all parameters serve as hyperpriors to inform person-specific parameter distributions for all parameters estimated (thus accommodating deviations among individuals in the sample) [50]. However, although CT-SEM allows for *quantitative* differences between individuals in the parameters of this model, the *qualitatively* different relationships between incidental affect and physical activity between participants are not easily interpretable [70]. That is, without supplementing the current analysis with cluster models [70] or recursive partitioning [71], we cannot ascertain whether particular subgroups of individuals differed in the functional forms of their dynamic relationships. For example, while some individuals may engage in MVPA as a form of "*affect regulation*," other individuals' dynamic relationships may be better explained by "*affect congruency*" [11] theoretical perspectives (e.g., on average, individuals who experience more positive incidental affective states engage in more MVPA).

Relatedly, CT-SEM analyses contain a stochastic element (i.e., the diffusion matrix), which partitions out variance associated with random fluctuations in both incidental affect and MVPA. This stochastic element also quantifies variability that is shared by common causes between the two variables. As evidenced by the diffusion matrix covariation in both the positive and negative affect models, some observed fluctuations in incidental affect and MVPA share common causes. In the physical activity domain, many other affective, cognitive, behavioral, and contextual factors are theorized to influence physical activity that fluctuate over time [72]. Accordingly, a critical next step for elucidating the continuous-time dynamics underlying physical activity and incidental affect would be identifying what factors (i.e., time-invariant or time-varying covariates) are associated with the shared fluctuations between the two variables.

Taken together, by identifying covariates associated with differences in effects between individuals (i.e., observed heterogeneity) and using analytical methods that accommodate qualitative differences in dynamics (i.e., mixture or recursive partitioning models), researchers will be able to identify subgroups of individuals who display similar affective dynamics. Knowledge of the unique affective dynamics underlying subgroups, in turn, has the potential to elucidate subpopulations where a physical activity intervention is beneficial or for whom it fails to work [73].

Conclusion

The results of the present study complement and build upon previous research examining the bidirectional relationships between incidental affective states and MVPA. Additionally, this study demonstrates that the use of continuous-time modeling is an innovative approach to provide nuanced insights into the affective dynamics underlying physical activity behavior. Particular insights revealed in this study include: (1) the existent of an eight-hour lag between incidental affective states and MVPA when the predictive relationships are strongest (both for affect predicting MVPA and vice versa), (2) the cross-lagged effects tend to persist to some extent over 30 h, and (3) the relationship between incidental affect states and MVPA differ depending on whether within- or between-person effects are considered.

Supplementary Material

Supplementary material is available at *Annals of Behavioral Medicine* online.

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Compliance with Ethical Standards

Authors' Statement of Conflict of Interest and Adherence to Ethical Standards Authors Geralyn R. Ruissen, Mark R. Beauchamp, Eli Puterman, Bruno D. Zumbo, Ryan E. Rhodes, Benjamin A. Hives, Brinkley M. Sharpe, Julio Vega, Carissa Low, and Aidan G. C. Wright declare that they have no conflict of interest. All procedures, including the informed consent process, were conducted in accordance with the ethical standards of the responsible committee on human experimentation (institutional and national) and with the Helsinki Declaration of 1975, as revised in 2000.

Primary Data The data reported in the current study were part of a larger program of research designed to use ambulatory assessment techniques (e.g., smartphone administered surveys, wearable technology) to study the daily dynamic processes of stress and responses to that stress, and how levels of personality and psychopathology amplify or dampen those processes. Findings related to the dynamic associations between emotion-based impulsivity and internalizing and externalizing psychopathology related to this dataset have been previously published elsewhere [43]. The findings related to the present study have not been previously published elsewhere. The authors have full control of all primary data and agree to allow the Journal to review data if requested.

Authors' Contributions G.R.R. conceptualized the current study and data analysis. C.A.L. and A.G.C.W. contributed to the conceptualization and study design of the larger AAPECS study. A.G.C.W., B.M S., and C.A.L. collected the data. B.M.S., B.A.H., and J.V. processed the data and performed preliminary statistical analyses. G.R.R. performed and interpreted the primary statistical analysis. G.R.R. and M.R.B. were involved in writing the first draft of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

Ethical Approval All procedures performed in this study were in accordance with the ethical standards of our institutional research ethics committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Slight deviation from this concerned informed consent, as explained below, but this was approved by our ethics committee.

Informed Consent Consent was obtained from all individual participants included in the study.

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