HHS Public Access
Author manuscript
Exerc Sport Sci Rev. Author manuscript; available in PMC 2018 January 01.

Published in final edited form as:
Exerc Sport Sci Rev. 2017 January ; 45(1): 48–54. doi:10.1249/JES.0000000000000092.

Ecological Momentary Assessment in Physical Activity Research

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Abstract

Theories explaining why individuals participate in physical activity often do not take into account within-person variation or dynamic patterns of change. Time-intensive methods such as Ecological Momentary Assessment (EMA) are more conductive to capturing time- and spatially-varying explanatory factors, and intraindividual fluctuations than traditional methods; and thus may yield new insights into the prediction and modeling of physical activity behavior.

Keywords

Ecological Momentary Assessment; physical activity; sedentary behavior; methods; health behavior theory; intraindividual variability; multilevel modeling

INTRODUCTION

Physical activity reduces risks of many serious health conditions, including coronary heart disease, type 2 diabetes, and breast and colon cancers (20). In order to achieve substantial health benefits, however, physical activity needs to be performed regularly over sustained periods of time. The 2008 Physical Activity Guidelines for Americans recommend that adults should accumulate at least 150 minutes per week of moderate-intensity aerobic physical activity or 75 minutes per week of vigorous-intensity aerobic physical activity (23). Aerobic activity should be performed in bouts lasting at least 10 minutes in duration and spread across the week. For maximum health benefit, regular physical activity should be maintained across the lifespan as an integrated component of one's daily or weekly routine. If physical activity levels decrease significantly below the recommended level for periods as short as two weeks, many of the cardiorespiratory benefits will diminish. Health benefits will disappear altogether within two to eight months of regular physical activity being halted (29).

Therefore, a defining feature of physical activity that sets it apart from other preventive health behaviors is that it should be performed on a frequent basis (i.e., every day or multiple times per day), and this behavioral practice should occur for extended periods of time—ideally across the entire lifespan. Given the amount of time, effort, and resources needed to

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maintain recommended levels of physical activity, it is not surprising that only about 1 in 5 U.S. adults meet the 2008 Physical Activity Guidelines at any given time (34), and this number is most likely much lower when considering adults who successfully maintain recommended levels of physical activity over multiple decades of their lives. Engaging in sustained daily physical activity may be particularly difficult due to day-to-day variations in how people feel, who they interact with, barriers they encounter, and where they find themselves. Maintaining consistency in behavior on a daily basis can be challenging when the conditions that influence that behavior fluctuate from day to day and across settings.

Limitations of Health Behavior Theories

There are a growing number of criticisms of traditional health behavior theories such as the Theory of Planned Behavior, the Health Belief Model, and Social Cognitive Theory, in part because they have been largely developed to explain *limited occurrence health behaviors* such as vaccinations and screenings, and do not apply as well *repeated occurrence health behaviors* such as physical activity. First, traditional health behavior theories often consider behavior as static phenomena examined at a single point in time, and fail to examine time itself as a covariate or the role of time-varying covariates. As a result, these theories typically focus on differences occurring between people (i.e., interindividual variation) instead of differences occurring within people or within days (i.e., intraindividual variation. Secondly, health behavior theories tend to overlook spatial and contextual influences on behavior. They typically fail to examine differences in behavior across settings and whether features of those settings are associated with changes in behavior. Third, theories do not incorporate concepts such as fluctuation or stability, or consider how these properties that may be predictive of behavior above and beyond the average levels of measured constructs. Taken together, these limitations may contribute to low predictive power of traditional health behavior theories in explaining repeated health behaviors such as physical activity (27).

Limitations of Traditional Physical Activity Research Methods

Weaknesses in health behavior theories may be in part due to limitations in the methods used to collect the empirical data supporting theory development and testing. Physical activity studies tend to employ cross-sectional, longitudinal, or experimental research designs where behaviors are measured on an infrequent basis (e.g., monthly or yearly) across a limited set of occasions (1). In these types of studies, physical activity measures are designed to capture an individual's *usual* level of physical activity on a typical day, week, or month; or the instrument scoring algorithm averages the reported values across several recent days to give an estimate of one's *usual* level of behavior (e.g., average daily minutes of moderate-to-vigorous physical activity). Either way, the outcome variable is typically an indicator of one's usual level of physical activity behavior at a single or limited set of time points; which not conducive to testing explanatory factors that vary frequently over time or space, and dynamic patterns of change and fluctuation. Methods of measuring physical activity may have been historically invariable in nature because the technologies did not exist to capture behaviors on a momentary basis or that the need simple wasn't fully realized because existing health behavior theories primarily offered static representations of behavior.

Advantages of Ecological Momentary Assessment

These methodological weaknesses may be addressed by through recent advancements in mobile and sensor technologies, which can collect information on physical activity behavior and its correlates using real-time data capture strategies such as Ecological Momentary Assessment (EMA) (30). In EMA studies, smartphones gather real-time self-reports of behaviors, contexts, emotional states, beliefs, attitudes, and perceptions in naturalistic settings. The use of EMA in physical activity research is growing rapidly as this time-intensive approach can supply novel insights into determinants of behavior. Mobile phones are becoming ubiquitous (22), and are easy to use; and thus have the capacity to collect data quickly from large numbers of people and transfer this information to remote servers in an unobtrusive way. EMA is thought to reduce recall errors and biases and enhance ecological validity because it collects self-reports more proximal to the time and place that behavior is occurring (28). EMA also provides momentary information about ongoing exposures, events, experiences, and behaviors; and produce repeated assessments to yield intensive longitudinal data (ILD). This paper provides support for the hypothesis that because of these unique features, EMA methods are more conductive to capturing phenomena that vary over time or space than traditional cross-sectional, retrospective, and summary methods. Therefore, EMA may yield new insights into the prediction and modeling of physical activity that build upon, and in some cases, challenge current assumptions generated from traditional methods. This paper will review research in the following three key areas that demonstrate how EMA may improve our understanding of physical activity behavior: 1) *Synchronicity*—the extent to which explanatory factors co-occur in time and space with physical activity behaviors; 2) *Sequentiality*—the temporal sequence of antecedents to and consequences of physical activity behaviors; and 3) *Instability*—patterns of fluctuation and change in explanatory factors and physical activity behavior (Fig. 1).

SYNCHRONICITY: TEMPORAL AND SPATIAL CO-OCCURRENCE WITH BEHAVIOR

Cross-sectional and longitudinal studies of physical activity typically focus on the person as the primary unit of analysis. Although this measurement approach can examine *inter-individual* (i.e., between-person) effects or differences, it is unable to determine whether there are also *intra-individual* (i.e., within-person) effects that operate across time and space. Preliminary research suggests that physical activity levels, affective states, beliefs, attitudes, and contextual exposures may vary considerably from across time (e.g., from day to day) and space (e.g., from setting to setting).(31) Yet, retrospective, summary, and infrequent measures of these constructs may conceal temporal and spatial variations. The failure to account for intra-individual variation is akin to committing an *ecological fallacy*—whereby inferences about the effects of variables at lower-level units of analysis (e.g., positive affective states) are based solely upon aggregate statistics collected for a higher unit of analysis (e.g., usual or average positive affect score for a person), potentially obscuring the true relationships. Furthermore, it is possible that a person's average or usual level of a construct does not reflect their instantaneous levels of at any given point in time or space.

EMA methods may address these types of unit of analysis problems that occur in physical activity research. Through the collection of repeated measures, EMA can capture between-person effects that occur at the level of the individual in addition to within-person effects occurring at lower units of analyses (e.g,, shorter time periods) that are conceptually nested within those individuals. Physical activity levels may vary across the day (or from place to place) as a result of variations in exposures, experiences, events, the onset of affective or physical feeling states, or the depletion/enrichment of cognitive resources occurring on similar time- and spatial-scales. Multilevel statistical modeling methods applied to EMA data can be used to disentangle these *within-subject effects* (i.e., deviations from one's own average level of a factor) from *between-subject effects* (i.e., deviations from the group average level of a factor) of time-varying correlates on physical activity (4). Differentiating within- versus between-subject effects of time- and spatially-varying covariates of physical activity is critical to understanding whether observed associations among constructs are driven by enduring individual differences or short-term reactions, or both

Temporal Synchronicity

In order to reduce potential ecological fallacies in physical activity research, study designs are needed that are able to test whether time-varying covariates and physical activity behaviors are *temporally synchronous* (i.e., co-occur in time). It may be falsely assumed that because a trait-level predictor variable (e.g., positive affect, low stress, self-esteem) is associated with individuals' overall levels of physical activity (32), that people experience those states in a systematic fashion before, during, or after physical activity episodes. However, it is possible that the relationships between these trait-level predictors and physical activity is confounded by other variables (e.g., self-regulation or self-efficacy) such that more physically active individuals have higher levels of these traits, on average compared to others, but they do not co-occur with changes in physical activity levels across the day or from day to day. EMA methods can be used to address these types of questions by investigating whether time-varying covariates and physical activity behaviors co-occur in time. For example, in an study of adults (M=40.3 years, 73% female), participants answered up to eight randomly-timed EMA prompts per day across four days (9). Each EMA prompt captured individuals' current activity level by self-report (coded as physically active vs not physically active), context (coded as outdoors or indoors), and negative affective state (e.g., anxious, sad, angry). Results found that there was a statistically significant within-subject effect for activity level on negative affect, indicating that when adults were more physically active than usual, they experienced more negative affect. However, this effect only occurred when physical activity was performed indoors (versus outdoors). These findings contrast other research studies examining between-subject effects, which have found that greater overall physical activity is linked to lower trait negative affect (16) and that individuals generally experience negative affective responses at higher physical activity intensity levels (10). This example demonstrates how using EMA to examine the temporal synchronicity of predictor variables and physical activity can yield information about the nature of the association between those constructs that differs from results generated by traditional methods.

Spatial Synchonicity

Ecological fallacies may also lead to incorrect assumptions about the extent to which spatially-defined factors such as contextual and environmental variables influence physical activity. There has been mounting evidence to suggest that physical activity levels may reflect features of the environments in which individuals live (5). Studies in this area typically examine the *availability of* and *access to* neighborhood environmental features or supports (e.g., parks, trails, sidewalks, recreational facilities) in relation to individuals' overall physical activity levels. However, most studies do not examine whether physical activity is *actually performed* in the setting with which it demonstrates an association (or alternatively, in an entirely different setting altogether). In other words, these type of studies fail to consider whether exposure to settings and the performance of physical activity behavior are *spatially synchronous* (i.e., occur in the same place). For example, studies have found that living in a neighborhood with a greater density of neighborhood parks is associated with being more physically active (2). However, without assessing where physical activity occurs, it cannot necessarily be assumed that that residents perform most or even some of their physical activity in those parks. The presence of neighborhood parks could be confounded by unmeasured environmental supports such as access to indoor sporting facilities such as health clubs and recreation facilities or the availability of home exercise equipment, which serve as alternative contexts for physical activity. This type of methodological limitation has been described by geographers as the uncertain geographic context problem (UGCoP) (14). The problem exists when there is uncertainty about 1) the exact setting that has a direct causal influence on the behavior and 2) the timing and duration of individuals' actual exposures to these contextual influences. Ignoring the UGCoP can potentially lead to flawed assumptions about where physical activity occurs and how environmental contexts can shape physical activity.

By collecting real-time self-report information about the spatial co-occurrence of behaviors and contextual exposures, EMA methods have the potential to address the UGCoP in physical activity research. EMA questions about what one is currently doing may be immediately followed up with the questions, "Where are you right now?" By doing so, they can be useful in describing the proportion of an individual's physical activity that actually takes place in particular context in relation to other contexts. This type of information can shed light on the relative importance of environmental correlates of physical activity identified through more traditional research methods. For example, studies such as Cohen and colleagues (2) have found that number of parks available within short distances of children's homes are positively associated with children's overall levels of moderate-to vigorous physical activity. This type of finding might lead the public health community to believe that children perform a substantial proportion of their physical activity at neighborhood parks. However, an EMA study of children (ages 9–13 years) found that only 16% of their physical activity was reported at a park or on a trail (8). Other common contexts for children's physical activity were at home (indoors) (30%), other outdoor locations (e.g. sidewalk, road, parking lot) (26%), front or backyard (at home) (8%), someone else's house (8%), at a gym or recreation center (3%), and other locations (9%). Additionally, this EMA study found that 47% of children's physical activity took place more than a few blocks from home, and that 67% of physical activity locations were traveled to by car. This example shows how EMA can provide information about the extent to which physical activity is performed in a particular context that challenges assumptions made by cross-sectional, summary-based research about the influence of that context on behavior.

SEQUENTIALITY: ANTECEDENTS TO AND CONSEQUENCES OF BEHAVIOR

In addition to examining synchronicity of phenomena, EMA methods can further be used to investigate the temporal sequence of *antecedents* leading to and *consequences* following physical activity episodes. EMA data may be collected in a time-intensive manner (across intervals ranging from minutes to hours) such that there are multiple records or observations made across each day of monitoring. The repeated measures sampling schemes allow researchers to examine lagged effects of time-varying factors such as affect, stress, cognitions, or social interactions on subsequent physical activity episodes measured at a later point (i.e., antecedents). EMA can also be used to examine the lagged effects of physical activities on subsequent psychological states or experiences measures at a later time point (i.e., consequences). By doing so, EMA methods can help to understand the potential causal sequences of events surrounding these behaviors.

Affective Antecedents and Consequences of Physical Activity Behavior

The ability to delineate the sequence of experiences leading up to and following behavior may be particularly informative for understanding the complex interrelationships between affective states, physical feeling states (e.g., energetic arousal, fatigue), and physical activity. A substantial body of evidence suggests that affective and feeling states such as stress and fatigue are linked to reduced physical activity (32). However, evidence is lacking on the directionality of acute effects of emotional states on physical activity and vice versa across time-scales as short as minutes and hours. For example, when children are feeling sad or tired, do they subsequently become less physically active (or when children are more physically active, do they become less sad)? Previous research on acute affective response to (i.e., consequences of) physical activity is typically conducted using experimental designs with structured exercise tasks in controlled laboratory settings (10). These methods are not conducive to allowing researchers to examine bidirectionality or emotional antecedents to physical activity because they are not designed to capture how incidental affective states are related to subsequent physical activity. To address this gap, an EMA study assessed ongoing affective states (positive and negative affect) and physical feeling states (tired and energetic) in children (ages 9–13 years). Participants received several randomly-timed EMA prompts per day during non-school time across four days. Levels of moderate-to-vigorous physical activity (MVPA) occurring in the 30 minutes immediately before or after each EMA prompt were measured by accelerometer (7). Results found that higher ratings of feeling energetic and lower ratings of feeling tired were associated with more MVPA in the 30 minutes after the EMA prompt. Also, MVPA in the 30 minutes before the EMA prompt was associated with higher ratings of positive affect and feeling energetic, and lower ratings of negative affect. Interestingly, there was not any evidence that short-term deviations in affective states led to subsequent changes in physical activity in children. Thus, physical feeling states (i.e., antecedents) predicted subsequent physical activity levels, which in turn, predicted subsequent affective states (i.e., consequences) in children. Findings from this type of EMA study may help to clarify questions about directionality left unanswered by cross-sectional and summary-based approaches to examining mental health and physical activity in children.

Cognitive Antecedents and Consequences to Physical Activity

Information about sequentiality provided by EMA may also shed important light on how behavioral cognitions such as self-efficacy, outcome expectancies, and intentions are related to physical activity behavior. Previous studies on the role of behavioral cognitions in physical activity behavior have focused almost exclusively treated them as static individual-level constructs that vary between (but not within people) (26). However, information is lacking on whether short-term variations in behavioral cognitions serve as antecedents to and consequences of changes in physical activity behaviors across the day. A recent study addressed this gap by using EMA methodologies in adults (M=40.3 years, 72.4% female). Participants answered up to eight randomly-timed EMA prompts per day across four days (24). At each EMA prompt, participants reported short-term physical activity self-efficacy (e.g., “Can you do at least 10 minutes of physical activity sometime within the next few hours even if you get busy?”). EMA also measured short-term physical activity outcome expectancies (e.g., “Doing 10+ min of activity in the next few hours would help me feel less stressed”). Short-term physical activity intentions were measured with the item, “I intend to be physically active for 10+ min. sometime within the next few hours.” At the same time, participants wore an accelerometer on their waist to capture MVPA occurring in the 120 minutes after each EMA prompt. Results indicated that higher short-term physical activity intentions, than average for a participant, predicted subsequent increases in MVPA over the next 120 minutes. However, these effects only emerged when short-term physical activity self-efficacy was higher than average for a participant as well. Short term outcome expectancies did not predict subsequent MVPA. Thus, short-term variations in intentions and self-efficacy may serve as antecedents to physical activity in adults. Although research is lacking on whether behavioral cognitions change after episodes of physical activity occur (i.e., serve as consequences of the behavior), further studies in this are important as there may be feedback loops linking changes in behavior with subsequent changes in cognitions, which may in turn lead to further changes in behavior across the day. This type of research could show that associations between behavioral cognitions and physical activity are not uniformly positive as previously thought, given that self-efficacy to perform subsequent physical activity may be lowered after a recent bout of physical activity.

INSTABILITY: FLUCTUATION AND ITS RELATION TO BEHAVIOR

Traditional assessment methods used in physical activity research that rely on measures that summarize usual levels of behavior and factors that correlate with behavior are unable to capture dynamic patterns of change over shortened time scales. As described above, psychological constructs such as self-efficacy, attitudes, mood, and activity levels may fluctuate across the day. The extent of fluctuation (i.e., degree of within-subject variation from the individual’s average level) in these factors may represent underlying trait-level patterns of *instability*. Two individuals may have the same average or usual level of a construct but display strikingly different levels of fluctuation or instability around that level. By collecting time-intensive repeated measures across acute time scales, EMA methods have the potential to capture fluctuation and instability in explanatory factors and in physical activity behavior itself.

Emotional Instability and Physical Activity

The capacity to capture instability in emotional states may yield additional insight in how affective factors may contribute to physical activity. Greater emotional instability is linked to disorganization and difficulty with planning and problem solving (17), which may explain its relation to a number of negative physical and psychological health conditions. However, research on how emotional instability may influence physical activity is lacking. When ILD in available for affective states, emotional instability can be modeled through a number of analytic approaches including the within-person variance, the first-order autocorrelation, the mean square successive difference, the probability of acute change, or mixed effects location scale modeling (13). For example, a recent study examined how individual differences in children's instability in affective and physical feeling ratings were associated with their overall levels of physical activity (7). Emotional instability was modeling using a mixed-effects location scale approach with PROC NLMIXED (Eq. 1), which included random effect for the within-subject (WS) variance (11). Doing so allows for the WS variance to vary across individuals, controlling for the effects of covariates on the WS variance.

$$\sigma^2_{\varepsilon_{ij}} = \exp(w'_{ij}\tau + \omega_i) \quad \text{(Eq. 1)}$$

where w denotes a vector of time-varying predictors and $\boldsymbol{\tau}$ stands for a vector of corresponding regression weights and ω represents a random effect. Results indicated that children with greater overall MVPA, as compared with others, showed significantly less instability (more stability) in positive and negative affect. However, mean levels of positive and negative affect were unrelated to overall MVPA, in contrast to prior work in this area (25). Emotionally stable children may have more psychological resources (e.g., coping mechanisms, self-esteem, optimism, subjective well-being) and higher executive functioning (35), which could facilitate planning and participation in health-enhancing behaviors such physical activity. Alternatively, physical activity could enhance mood regulation capabilities through neurocognitive pathways (33). Although the cross-sectional design of this study prevents definitive conclusions about the directionality of the relationship between emotional instability and lower levels physical activity in children, this investigation highlights the potential of EMA for examining patterns of fluctuation in key behavioral determinants.

Instability in Behavioral Cognitions and Physical Activity

EMA methods may also be used examine how variability and instability in behavioral cognitions such as beliefs about one's abilities or expected benefits predict physical activity behaviors. In the study of adults described above (24), EMA was used to examine whether instability in behavioral cognitions was associated with overall physical activity in adults.

Mixed-effects location scale modeling found that although person-level average self-efficacy was unrelated to total MVPA, individuals who demonstrated more instability in self-efficacy performed more MVPA overall. The same patterns emerged for intentions, with greater instability in intentions predicting higher levels of MVPA in the absence of a relation between average intentions and MVPA. These findings stand in contrast with other research indicating that greater volatility in cognitive and affective factors may be detrimental to behavior and health outcomes (21). It is possible that instability in psychological constructs may not be uniformly maladaptive for performing positive behaviors. When examining across finer-grained time scales such as every few hours, instability in behavioral cognitions may indicate realistic evaluations of one's ability to successfully perform a behavior given the current circumstances. Individuals who are more physically active may have a more realistic understanding of the conditions under which they will be able (and not able) to perform the behavior, which would manifest as unstable behavioral cognitions. The fact that the degree of instability in self-efficacy and intentions explained overall physical activity to a greater extent than mean levels of the same constructs highlights the value of considering instability in future models of physical activity.

FUTURE DIRECTIONS

In addition to the areas highlighted above; a number of analytic methods can be applied to the ILD obtained from EMA methods to answer important substantive questions about physical activity. A few examples are described here.

Time-varying Effects of Physical Activity Correlates

Traditional approaches to multilevel modeling typically aggregate associations between time-varying predictors and outcomes across the monitoring period of the study to generate a mean level of association over time for each person. In future applications, EMA data from physical activity studies can be modeled with novel non-linear statistical methods such as time-varying effect models (TVEM) (15) to determine whether the magnitude and direction of the associations between psychosocial factors and subsequent physical activity vary systematically by the time of day. By doing so, they can identify windows of opportunity or vulnerability across the day where time-varying predictor variables have greater influence over physical activity.

Reciprocal Relationships and Feedback Loops

Reciprocal relationships and feedback loops may be uncovered through the repeated assessment protocols of EMA methods. For example, applying computational strategies such as Dynamical Systems Modeling (DSM), developed from control systems engineering, can allow researchers to capture the speed, shape, and magnitude of responses through a system of ordinary differential equations (19). Applying DSM approaches to EMA data from physical activity studies offers many advantages over traditional multilevel regression modeling for handling nonlinear effects, bidirectionality and temporal feedback loops, and variations among system components over time.

Dyadic and Social Network Analyses

Dyadic and social network analytic approaches can be applied to EMA data to investigate the interpersonal effects of time-varying predictor variables on physical activity among two related members of a dyad (e.g., mother and child, romantic partners) or from multiple members of a social network (e.g., entire classroom or dormitory floor). The Actor-Partner Interdependence Model (APIM) (3) framework can be used to assess bidirectional effects in interpersonal relationships when similar constructs are measured from interrelated yet distinguishable members of a dyad. The APIM has the ability to disentangle intrapersonal or actor effects (how much an individual's thoughts or attitudes influences his or her own behavior) from interpersonal or partner effects (how much an individual's thoughts or attitudes influence his or her partner's behavior) at the within-subjects and between-subjects level. Additionally, social network analytic strategies can be applied to EMA data to understand how individuals within a group affect each other's behavior in dynamic ways over time.

Context-sensitive EMA

Most EMA studies of physical activity and diet use signal-contingent EMA sampling procedures, which trigger surveys at random times throughout the day. The limitation with this approach is that even when surveys are prompted frequently, signal-contingent sampling strategies may fail to capture rare exposures or outcomes such as MVPA bouts. To address this problem, sensor-informed context-sensitive Ecological Momentary Assessment (CS-EMA) apps have been developed for Android smartphones (6). These types of program use the phone's builtin motion sensor to automatically detect periods of motion, inactivity, or no data from the phone. The app then uses these sensor-informed cues to trigger real-time CS-EMA surveys to assess characteristics and contexts of, and responses to physical activity and sedentary behavior.

Just-in-Time Adaptive Interventions (JITAIs)

Ultimately, information provided through EMA on complex relations between time-varying predictors and physical activity can form the basis of Just-In-Time Adaptive Interventions (JITAIs) (18). JITAIs are based on decision rules for determining when, where, and how interventions (i.e., recommendations, information, nudges) should be delivered in order to have optimal impact (12). Data collected through EMA can inform the development of intervention content and messages, as well as timing of intervention delivery for JITAIs targeting physical activity change.

CHALLENGES AND LIMITATIONS

Although EMA offers a number of advantages for addressing questions pertaining to time-varying covariates in physical activity research, it comes with some challenges. First, there may be missing data, which complicate the data analysis process. Data may not be available for a number of reasons, such as participants not carrying the smartphone when being physically active; participants being unable to or not wanting to respond to EMA prompts due to competing activities; and technological issues such as battery drainage and software malfunction. A second set of challenges for EMA studies of physical activity involves potential reactance to survey questions and participant burden. Although the goal of most EMA studies is to observe behavior without influencing it, repetitively being asked about physical activity may cause participants to think about the behavior differently or change behavior. Participant burden can also limit the quality and quantity of data collected in EMA research. The frequency of prompting should depend on the time-scale of variation in the phenomena of interest. If the rate of prompting is too high and questions are too repetitive, participants may opt not to respond to the surveys or drop out of the study altogether. Other problems include the mindless answering of EMA items, choosing the first response option for every item to finish faster, or handing the phone off to another person to complete the questions because the participant has become bored or no longer wants to complete the items.

SUMMARY AND CONCLUSIONS

The requirement of repeated performance over extended periods of time in the context of ever-changing psychological, social, and situational dynamics make the maintenance of regular physical activity an incredible challenge. Health behavior theories may have limited predictive ability to explain repeated health behaviors such as physical activity because they fail to examine time itself as a covariate or other time-varying covariates, overlook differences in behavior across settings, and do not incorporate concepts such as fluctuation or stability. Weaknesses in health behavior theories may be in part due to shortcomings in the methods used to develop them, which include retrospective and summary measures of usual behavior. The goal of this review was to provide evidence from published studies that because EMA collects real-time, real-world, repeated measures information; it is more conductive to capturing phenomena that vary over time or across space than traditional methods. Therefore, EMA has the potential to yield new insights into the prediction and modeling of physical activity that build upon, and in some cases, challenge current assumptions generated from traditional methods. The objective of this review was not to recommend that EMA be used as a replacement for traditional research methodologies in all situations. Instead, it is recommended that EMA methods be considered as an alternative or additional assessment tool, especially when there are research questions pertaining to time- or spatially-varying predictors of physical activity. Evidence provided in this review highlights key areas such as answering questions about synchronicity, sequentiality, and instability where EMA methods can shed new light on the complexities of physical activity behavior. As EMA methods are more widely adopted in physical activity research, it is expected that they will lead to innovations in theory development, etiology and mechanistic insight, and intervention design that will significantly advance the field.

Acknowledgments

Funding: R01HL119255, R01HL121330, R21HL108018; American Cancer Society Grant 118283-MRSGT-10-012-01-CPPB; Robert Wood Johnson Foundation Grant 65837 Conflicts of interest: None

The author thanks Jaclyn Maher, PhD for providing feedback on earlier drafts of this paper.

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KEY POINTS

- In order to reduce chronic disease risk, physical activity behaviors should be performed repeatedly on a daily or within-daily basis.
- Most theories and methods used to explain why individuals participate in physical activity do not take into account within-person variation or dynamic patterns of change.
- These criticisms may be addressed by collecting information on physical activity behavior and its correlates in a time-intensive manner using Ecological Momentary Assessment (EMA).
- In EMA studies, smartphones gather real-time self-reports of behaviors, contexts, emotional states, beliefs, attitudes, and perceptions in naturalistic settings.
- EMA methods can allow researchers to take advantage of recent advancements in mobile and sensor technologies to yield innovative insights into the complexities of physical activity behavior.

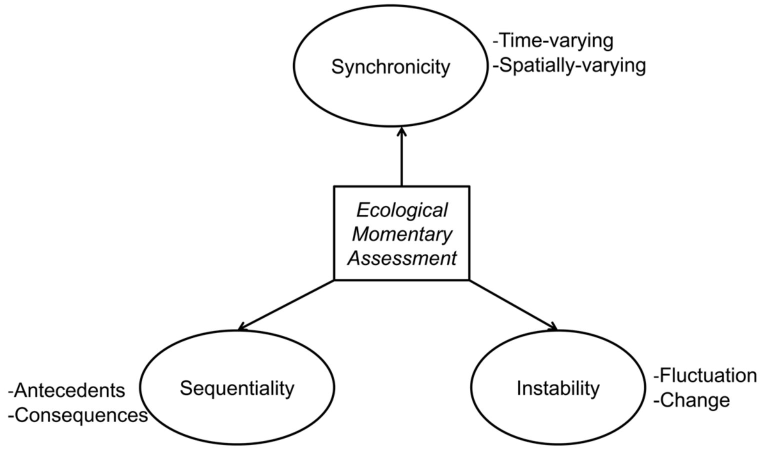

Figure 1.

Key areas that illustrate how Ecological Monentary Assessment (EMA) methods may improve understanding of physical activity behavior. Each area focuses on a different type of conceptual relationship between time, explanatory factors, and physical activity. *Synchronicity*— the extent to which explanatory factors co-occur in time and space with physical activity behaviors. 2) *Sequentiality*—the temporal sequence of antecedents to and consequences of physical activity behaviors. 3) *Instability*—patterns of fluctuation and change in explanatory factors and physical activity behavior.