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COMMENTARY/POSITION PAPER

How intensive longitudinal data can stimulate advances in health behavior maintenance theories and interventions

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Abstract

Interventions that promote long-term maintenance of behaviors such as exercise, healthy eating, and avoidance of tobacco and excessive alcohol are critical to reduce noncommunicable disease burden. Theories of health behavior maintenance tend to address reactive (i.e., automatic) or reflective (i.e., deliberative) decision-making processes, but rarely both. Progress in this area has been stalled by theories that say little about when, why, where, and how reactive and reflective systems interact to promote or derail a positive health behavior change. In this commentary, we discuss factors influencing the timing and circumstances under which an individual may shift between the two systems such as (a) limited availability of psychological assets, (b) interruption in exposure to established contextual cues, and (c) lack of intrinsic or appetitive motives. To understand the putative factors that regulate the interface between these systems, research methods are needed that are able to capture properties such as (a) fluctuation over short periods of time, (b) change as a function of time, (c) context dependency, (d) implicit and physiological channels, and (e) idiographic phenomenology. These properties are difficult to assess with static, cross-sectional, laboratory-based, or retrospective research methods. We contend that intensive longitudinal data (ILD) collection and analytic strategies such as smartphone and sensor-based real-time activity and location monitoring, ecological momentary assessment (EMA), machine learning, and systems modeling are well-positioned to capture and interpret within-person shifts between reactive and reflective systems underlying behavior maintenance. We conclude with examples of how ILD can accelerate the development of theories and interventions to sustain health behavior over the long term.

Keywords

Intensive longitudinal data, Methods, Health behavior, Maintenance, Theory, Intervention

Implications

- With intensive longitudinal data (ILD) methods, new theories of health behavior maintenance can be developed and tested that define progression, stagnation, and regression along the behavior change continuum based on the nature of the interplay between reactive and reflective systems that guide behavior.
- ILD methods can be used to evaluate when shifts from reactive- to reflective-based strategies or vice-versa were successfully achieved—becoming a new set of benchmarks to determine the efficacy of behavior maintenance interventions.
- ILD may enable a new class of computer-driven, just-in-time adaptive interventions that deliver tailored, momentary intervention content at the same temporal scale as the reactive and reflective factors that are influencing the behavior.

INTRODUCTION

A substantial portion of the noncommunicable disease burden is attributable to a set of common health risk behaviors (e.g., low physical activity, high sedentary behavior, poor sleep, unhealthy diet, and tobacco and alcohol use) [1]. This challenge is well-recognized, and worldwide, public health strategies aim to prevent, reduce, and eliminate these patterns of health risk. Yet, the specification of effective intervention strategies has proven difficult, in no small part because the health benefits afforded by engaging in sufficient levels of physical activity and sleep, eating healthy, and avoiding tobacco and alcohol require sustained engagement with these behaviors on a daily or sub-daily basis across months and years. There is a need for new insights into the mechanisms that underlie sustained patterns of behavior to inform the development of public health strategies that can reduce the enormous costs of noncommunicable disease.

Limited intervention success at promoting long-term health behavior maintenance

Interventions to reduce noncommunicable disease have been relatively successful at helping individuals make initial changes in health behaviors [2]. These programs seek to move people from an unhealthy state towards a healthy state, supporting the initiation of new health-enhancing behaviors (e.g., physical activity or healthy eating) or the reduction of existing health-damaging behaviors (e.g., tobacco or excessive alcohol use). Less is known, however, about how to keep people in that healthy state once they get there. After an intervention, people often fail to maintain healthy patterns of behavior long term, and they typically regress back to initial levels. Lapses in health behaviors, even for short periods of time, can have negative physical and mental health

consequences in themselves. Of greater concern, they can increase vulnerability to permanent failure to re-engage in the behavior (i.e., relapse). Lapses and relapses are frequent among individuals attempting to maintain health behaviors. For example, a study of overweight postmenopausal women, 61% had one or more physical activity lapses (i.e., period where they stopped exercising ≥ 2 weeks) across a 6 month period, and 39% did not resume physical activity after the lapse [3]. Additionally, overweight dieting adults reported an average of six diet lapses (i.e., an incident where they felt that they broke their diet) across a 7 day study [4]. Intervention developers need information about the precursors of these lapses and how to best help individuals either avoid them or keep them from turning into relapses.

Theories of health behavior maintenance

The inability of health behavior interventions to promote long-term health behavior maintenance may be tied to the lack of strong theories that focus on the maintenance of a positive health behavior change. Interventions are designed based upon theory, which guides program design, implementation, and evaluation. The first generation of health behavior theories (e.g., the theory of planned behavior, the health belief model, and social cognitive theory) focused primarily on understanding why people do or do not initiate a new pattern of behavior. These types of theories emphasize social-cognitive constructs as important drivers of behavior change and targets for intervention; targets include attitudes towards a behavior, expected behavioral outcomes, confidence to perform a behavior, formation of an intention to perform the behavior, and planning towards the implementation of those intentions. The first generation of health behavior theories assume that patterns of sustained behavior reflect either the effect of prior behavior or the same set of determinants that guided the initiation of the new pattern of behavior.

Over the past two decades, there has been a growing interest in characterizing the determinants of health behavior maintenance. Unlike early health behavior initiation theories that focused on the content of cognitions, recent theories that seek to explain behavior maintenance focus on the psychological processes underlying behavior. New theories of health behavior maintenance are based upon constructs that were overlooked by the previous generation of health behavior theories such as contextual factors, motives, self-regulation, habits, and psychological and physical resources [5]. Many of these new generation health behavior maintenance theories address processes that can be categorized into one of two general types of psychological systems described collectively as dual-processes models of decision-making and behavior [6]. The first system involves reactive processes that are fast, automatic, and efficient. Theories on behavioral habits, for example, delineate how nonconscious processes can help explain long-term behavior maintenance [7]. Habits are thought to develop gradually through experience as people repeatedly perform a rewarding action in a stable place, time, or other context—which becomes a nonconscious cue for behavior. Furthermore, affect- and motivation-based theories such as Incentive Salience Theory [8] and Hedonic Motivation [9] posit that attitudes towards behavior, urges, cravings, and desires can support behavior maintenance through processes that operate outside of conscious awareness. The second type of system involves reflective processes, which are slow, deliberative, and effortful. Reflective processes include the self-regulatory efforts that people exert to translate intentions to inhibit urges towards unwanted actions into behavior; they do this through self-monitoring, self-evaluation, self-reinforcement, and self-control. Reflective processes that contribute to health behavior maintenance are described by theories such as the Health Action Process Approach [10] and Carver and Scheier's Control Theory [11], for example. In general, theories of health behavior maintenance tend to be based upon, or address, reactive processes or reflective processes, but rarely both.

Understanding the interplay between reactive and reflective processes in health behavior maintenance

Theories that address the interplay between reactive and reflective processes in promoting health behavior maintenance are limited. The Physical Activity Maintenance (PAM) Theory [12] posits that reactive processes (such as contextual triggers and stress) can support or inhibit physical activity maintenance either directly or indirectly through reflective processes (such as goal-setting, motivation, and self-efficacy). Likewise, Rothman's theory of maintenance [13] suggests that reflective processes (such as self-efficacy) play a larger role during the early stages of behavior maintenance—shortly after initial adoption—when the health behavior is still new, and deliberative effort is still required to inhibit the prior pattern of unhealthy behavior. In the later stages of behavior maintenance, engaging in the behavior may require less deliberative effort as the pull of the prior behavior wanes, and the repeated pairing between contextual cues and health behavior facilitates reactive processes (such as perceived satisfaction with behavior). These theories broadly recognize the potential joint contributions of reactive and reflective processes to support behavior maintenance and in doing so have expanded how researchers have conceptualized these underlying processes. However, neither theory is able to specify the nature or timing of the interplay between reactive and reflective processes. For example, do individuals simultaneously rely on both

types of systems to regulate their behavior, are they engaged sequentially across different timescales, or does one system predominate and the other is used only if needed? With an evidence base that delineates when, where, why, and how reflective and reactive processes are jointly engaged to promote (or derail) maintenance of positive behavior change, interventions can be developed to target these processes, affording the possibility of promoting superior long-term success rates.

Building upon this premise, we propose that on the micro-temporal level (across minutes, hours, and days) there may be occasional, temporary shifts back and forth between reflective and reactive processes that need to occur to sustain successful maintenance. These micro-temporal shifts likely differ within and across people. Progress in health behavior maintenance research, however, has been stalled by theories that say little about when, where, and why shifts occur between the reactive and reflective systems, and how these two systems work together to synergistically support behavior maintenance. Discussed below are factors assumed to influence the timing and circumstances under which an individual may rely on one system over the other or shift between the two systems. As noted below, we propose that certain patterns of shifting between reactive and reflective processes may be instrumental toward determining whether an individual will maintain a positive behavior, or whether lapses into previously established negative behaviors will ultimately lead to failure to maintain positive behavior. Small lapses that cannot be handled with reflective processes may translate into full blown relapses of the previously-held, health-damaging behavior pattern.

Limited availability of psychological assets

The capacity for reflective decision-making is thought to depend on access to cognitive and emotional resources such as attention, focus, emotional regulation, and physical energy. These psychological assets can be depleted when an individual is stressed, fatigued, in pain, overloaded, distracted, or exhausted [14]. When psychological resources are less available, the reflective system may be insufficient to maintain behavior. In these situations, having stronger habits that are triggered automatically, with low effort through the reactive system, may lead to greater behavior maintenance success.

Interruption in exposure to established contextual cues

The maintenance of behavior is thought to be supported through reactive processes when contextual cues for the behavior are encountered consistently (e.g., a person always goes to the gym immediately after work) [7]. However, when there is a change in environment or routine such as weather, travel, cancelled plans, or life transitions (e.g., moving, new job, birth of a child), the reactive system is disrupted, thereby leaving an individual susceptible to a lapse. Moreover, the lapse may activate old and counterproductive reactive processes. For example, when one is traveling for work, he or she may not have access to a gym for exercising. In these situations, the successful maintenance of health behavior may rely on the activation of reflective processes for problem-solving, planning, and controlling urges to revert to prior (or new) unhealthy habits.

Lack of intrinsic or appetitive motives

Individuals are thought to continue behaviors that are intrinsically motivating (i.e., bring them enjoyment and satisfaction) [15] or driven by appetitive motives (i.e., drive towards pleasure). Rewarding experiences such as positive affect while performing the behavior (e.g., fun, relaxation, and pride) or fulfillment with the outcome of the behavior (e.g., successful weight loss and better sleep) reinforce future engagement in that behavior. However, intrinsic motivation and appetitive motives may fluctuate due to unpleasant experiences with the behavior (e.g., pain, boredom and withdrawal symptoms) or dissatisfaction with the outcome (e.g., lack of weight loss and injury). When intrinsic motivation and appetitive motives are lacking, individuals may need to rely on the reflective system by employing processes such as self-regulation, self-control, planning, and the inhibition of urges.

Taken together, these factors may indicate when people need to shift (or cause them to shift) from one system to another (and possibly back again) to maintain behavior. Currently, most theories that have been proposed or used to explain health behavior maintenance do not address or specify these system dynamics. Progress in this area has been hampered by data acquisition and analysis methodologies that can neither capture how the reactive and reflective systems interface with each other over time nor identify the factors that cause shifts from one processing system to the other either to sustain maintenance or derail it.

How intensive longitudinal data can enhance understanding of health behavior maintenance

Factors that dynamically influence when an individual may shift between the reactive and reflective systems have properties that make them difficult to assess through static, cross-sectional, laboratory-based, or retrospective research methods. The emergence of intensive longitudinal data (ILD) methods, which collect and analyze high-frequency and high-density data across micro timescales (e.g., seconds, minutes, and hours) in real-world settings, may enable measurement of dynamic processes guiding the interplay between reactive and reflective systems. Enhanced miniaturization, capability, affordability, and pervasiveness of mobile and wearable devices in recent

years has facilitated the acquisition of ILD through passive assessment strategies such as the monitoring of body movement, biological responses, geographic location, phone/app use, social interactions, and communication patterns. ILD can also be acquired actively via self-report through ecological momentary assessment (EMA) of psychological constructs such as affect, motivations, and cognitions. Although investigators need to be mindful that psychological measures may need to be re-validated for use in an EMA context. Finally, passive and active methods can be combined, such as context-sensitive EMA [16] and micro-interaction EMA, to enable high-temporal-density measurement of comprehensive behavioral and contextual states.

Furthermore, advancements in data science, machine learning, and systems modeling provide new tools for interpretation of ILD and modeling of the behaviors that led to it. These models can be used to describe and predict dynamical patterns of change. Below, we describe how such ILD methodologies might enhance our ability to capture dynamic shifting between reactive and reflective systems that occurs during health behavior maintenance. ILD methodologies are well-suited to capture the unique properties of factors that regulate the interface between the reflective and reactive systems in behavior maintenance. These properties include (a) fluctuation over short periods of time, (b) change as a function of time, (c) context dependency, (d) implicit and physiological channels, and (e) idiographic phenomenology.

Fluctuation over short periods of time

The timing of whether reactive or reflective systems are activated may depend on variations in psychological factors such as motives, affective states, stress, and self-control, as well as changes in exposure to environmental facilitators or barriers to engaging in the behavior. These factors may fluctuate (i.e., increase and decrease) within individuals across short periods of time such as seconds, minutes, or hours. For example, positive emotional states may wax and wane across the day as an individual encounters different situations and triggers. ILD methods that collect data across micro-temporal intervals are well-suited to capturing dynamics of these fluctuations such as reactivity (i.e., peak change from baseline), duration of recovery (i.e., time to return to baseline), and overall stability (i.e., degree of variation within an individual). Cutting-edge ILD analytic strategies such as Mixed-Effects Location-Scale Modeling [17] and Time Varying Effects Modeling (TVEM) [18] can be used to quantify within-day fluctuations in levels and effects. In contrast, retrospective, survey-based methodologies are generally limited to capturing variability down to the day level at best.

Change as a function of time

Another key property of factors that affect the interplay between reflective and reactive systems is the way that change manifests as a linear or curvilinear function of time itself (e.g., across days and weeks). For example, psychological resources such as self-control may be depleted across a day with accumulated exposure to stressors or other demands. Also, enjoyment of exercise may grow over a few weeks as an individual improves cardiovascular and muscular fitness. ILD collected continuously or intermittently can capture important dynamics of these time-dependent processes such as rates of change (i.e., amount of change over time), acceleration (i.e., rate of increase in rate of change over time), and deceleration (i.e., rate of decrease in rate of change over time).

Context dependency

Whether reflective or reactive processes are used to maintain behavior may depend upon the social and physical context in which the behavior is performed. For example, an individual may regularly purchase a healthy salad from a cafeteria at work. In this situation, the routine of going to the same place and ordering the same thing cues reactive processes that support the healthy behavior. However, if the cafeteria is closed on a particular day, reflective processes such as self-control and inhibition may be necessary to avoid a diet relapse. ILD that are collected passively and objectively through smartphone and smartwatch devices can be used to paint a more complete picture of the array of contextual features that trigger these reactive and reflective processes. For example, sensors built into smartphone and smartwatch devices can collect continuous streams of data on body movement (e.g., via accelerometers), geolocation (e.g., via location systems), and possible social interactions (e.g., via radio identification of nearby phones). Also, it is possible to monitor the timing and duration of application use, noise and light exposure, and communication patterns (e.g., texts, voice calls) on smartphones and smartwatches to gather further sources of contextual data.

Implicit and physiological channels

Factors that regulate shifts between reflective and reactive systems may unfold implicitly or physiologically—outside of conscious awareness. For example, implicit appetitive motives (i.e., drive to satisfy a need) may operate automatically without conscious cognitive interpretation such as the urge to smoke or craving for a high sugar food. Also, heart-rate variability may indicate the depletion of psychological resources to a greater degree than what one can self-report. These processes are typically assessed through one-time, laboratory-based measures such as computer-administered implicit tasks (e.g., testing

cognitive associations between words and images) or psychophysiological instruments (e.g., heart rate and electrodermal). ILD methods can be useful for assessing naturalistic variation in these processes through smartphone- or smartwatch-based versions of implicit tasks or embedded physiological sensors that collect repeated assessments in real-world settings.

Idiographic phenomenology

The conditions under which reactive and reflective processes are triggered may vary in different ways across different people based on individual preferences, abilities, and constraints. For example, one person may switch from reactive to reflective decision-making to exercise when the context changes due to bad weather, whereas another person may need to make that shift when they have a negative experience with exercise such as an especially tough workout on the previous day. ILD are particularly useful for identifying idiographic (i.e., person-specific) patterns in behavior. Each person needs many data points, and ILD can give hundreds or thousands of observations per person in a single study. Idiographic analytic approaches such as machine learning methods, agent-based modeling, and dynamic systems modeling can be applied to ILD to identify person-specific combinations of factors that influence health behavior maintenance [19]. However, researchers need to develop better ILD analytic methods for examining dynamic mediational pathways and interactions between reactive and reflective factors.

Applications of ILD to health behavior maintenance theories and interventions

ILD methodologies can be applied in a variety of ways to advance theories and interventions targeting health behavior maintenance. Stage theories of health behavior change that typically classify individuals along the behavior change continuum (from adoption through maintenance) based on the duration of time a behavior has been performed certainly do not apply to all behaviors or all individuals in the same way [20]. With ILD methods, new theories of health behavior maintenance can be developed and tested that define progression, stagnation, and regression along the behavior change continuum based on the nature of the interplay between reactive and reflective systems that guide behavior. For example, if an individual demonstrates a shift to primarily reactive (or habitual) processes that influence behavior maintenance, the individual may be considered to have progressed along the behavior change continuum to later stages of behavior maintenance. However, failure to make this shift or a permanent reversion to reflective processes may indicate stagnation at the earlier stages of maintenance or regression along the continuum. Thus, ILD can generate more sensitive indicators of behavior change that are independent of the amount of time one has been engaging in the behavior, distinct from actual observable levels of engagement in behavior, and variable across people. A goal of future work could be to develop a timeline that begins to delineate the how the interface between reflective and reactive systems in behavior maintenance unfolds over different time scales and time-ordering effects.

Additionally, ILD can facilitate the development of new targets and evaluation benchmarks for health behavior maintenance interventions. With assistance from ILD, periods when an individual is vulnerable to lapse or relapse (such as when contexts change, appetitive motives are weak, or psychological assets are low) can be identified. During these high-risk periods, intervention strategies can be delivered that help individuals shift from reactive- to reflective-based strategies or vice-versa in order to maintain behavior. ILD methods can then be used to evaluate when these shifts in strategies were successfully achieved—becoming a new set of benchmarks to determine the efficacy of behavior maintenance interventions.

Furthermore, if it is discovered that rapid fluctuations in context or behavior impact reactive and reflective processes and, thus, behavior maintenance, automated processing of ILD data—in combination with new theory—may enable a new class of computer-driven, just-in-time adaptive interventions. These new interventions, made possible only with wearable and mobile technologies, could deliver tailored, momentary intervention content at the same temporal scale as the factors that are influencing the behavior. Thus, rather than addressing what might be a reactive problem with a reflective solution, it may be possible to influence reactive behavior with reactive intervention, and reflective behavior with reflective intervention.

CONCLUSION

Progress in health behavior maintenance intervention research has been stalled by theories that say little about when, why, where, and how individuals alternate between reflective and reactive systems to sustain behavior. In this commentary, we have argued that ILD strategies are well-positioned to capture the dynamic processes guiding the interplay between these two systems. The application of ILD methodologies in health behavior research will yield new insights into the fundamental structure of health behavior maintenance theories. Research advances in this area will pave the pathway to building more predictive models and effective interventions to prevent behavior lapse and conversion to relapse.

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Compliance with Ethical Standards

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