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Leveraging Intensive Longitudinal Data to Better Understand Health Behaviors*

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Abstract

Behavioral scientists have historically relied on static modeling methodologies. The rise in mobile and wearable sensors has made intensive longitudinal data (ILD)—behavioral data measured frequently over time—increasingly available. Consequently, analytical frameworks are emerging that seek to reliably quantify dynamics reflected in these data. Employing an input-output perspective, dynamical systems models from engineering can characterize time-varying behaviors as *processes* of change. Specifically, ILD and parameter estimation routines from system identification can be leveraged together to offer parsimonious and quantitative descriptions of dynamic behavioral constructs. The utility of this approach for facilitating a better understanding of health behaviors is illustrated with two examples. In the first example, dynamical systems models are developed for Social Cognitive Theory (SCT), a prominent concept in behavioral science that considers interrelationships between personal factors, the environment, and behaviors. Estimated models are then obtained that explore the role of SCT in a physical activity intervention. The second example uses ILD to model day-to-day changes in smoking levels as a craving-mediated process of behavior change.

I. Introduction

Historically, accurately quantifying human behavior with respect to time had met with limited success. This is largely due to methodological challenges associated with frequent measurement of behavioral constructs, which helped lead to behavioral science research's reliance on tightly controlled laboratory or clinical settings and correlational epidemiological studies for studying behavior change. As a result, hypothesized mechanisms of behavior change have largely emerged from static analyses of cross-sectional data [1].

Recent advances in mobile technologies (e.g., smart phones) and wearable sensors (e.g., wearable accelerometers) have facilitated cost-effective collection of what behavioral

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scientists call “intensive longitudinal data” (ILD)—frequent measurements of behavioral constructs (e.g., how long an individual engages in physical activity, levels of motivation to engage in physical activity), including continuous-time and real-time measurement of behaviors [2], [3]. With the rise in the availability of ILD, behavioral scientists have been increasingly pursuing opportunities to better understand how behaviors and related constructs change over time and how exogenous variables such as environmental factors and therapeutic interventions affect these dynamics. Furthermore, ILD offers a means to develop richer descriptions of theorized behavior change mechanisms, which could help validate and guide revisions to such hypothesized mechanisms.

Contrasting traditional statistical behavioral science methods, analytical frameworks have recently emerged that are better suited to model dynamic phenomena captured in ILD. Methods from engineering offer one such approach for characterizing dynamic behaviors as *processes* of change [1], [4], [5]. Specifically, continuous-time differential equation models that employ an input-output perspective—i.e., *dynamical systems models*—are well suited for such analyses. For example, recent work estimated low order differential equations to describe dynamics observed in pain management [4], smoking cessation [5], and physical activity intervention [1] studies. The dynamic models developed in these efforts draw from ILD and parameter estimation routines from *system identification* to estimate gains, which quantify the net response of a behavioral outcome variable (e.g., duration of daily physical activity, self-reported urge to smoke cigarettes) to unit changes in input variables (e.g., unit doses of behavioral counseling intended to promote healthy behaviors), time constants, which quantify the speed of the outcome variable's response, system zeros, which indicate shape of response, and more [6], [7]. Employing this approach to characterize time-varying behaviors benefits from the fact that system identification routines are reliable and mature, having been applied within engineering settings for decades [6], [7], and have been precoded in commercially-available products such as MATLAB [7], [8]. Furthermore, dynamical systems models often act as the basis for the design of control algorithms that seek to automate optimal operation of industrial systems; the connection to control theory suggests that incorporating this engineering modeling approach into behavioral science settings offers the opportunity to develop novel closed-loop behavioral interventions (see [1], [5] and articles referencing [4], [9]).

Through two case studies, this article summarizes the usefulness of dynamical systems modeling and system identification for leveraging ILD in order to better understand human behavior change: Section II outlines a dynamical systems approach for characterizing Social Cognitive Theory—an influential concept in behavioral science that is based in learning theory [10]—in the context of a physical activity intervention (described in detail in [1]); Section III describes use of an engineering approach for examining smoking behavior change and the role of statistical mediation—a hypothesized mechanism of change commonly studied in the social and behavioral sciences [11] (described in detail in [5]); finally, Section IV comments on future research.

II. Case Study I: Social Cognitive Theory & Physical Activity Behaviors

Growing out of learning theory, Social Cognitive Theory (SCT) revolves around the idea of triadic reciprocity, which considers inter-relationships between personal factors (e.g., cognition, biology), the environment, and behaviors, seeking to explain how internal and external factors lead an individual to engage in target behaviors [1], [10]. Specifically, there are five fundamental components of SCT, which are seen as outputs in a dynamical systems sense (referred to as $\eta_{1...6}$); SCT attributes changes in these components to eight external and internal factors, which are treated as exogenous inputs in dynamical systems models (represented as $\xi_{1...8}$):

- *Self-management skills* (η_1) - complex set of behaviors that increases an individual's potential for engaging in a target behavior, e.g., self-monitoring, goal setting.
- *Outcome expectancy* (η_2) - perceived likelihood that performing a target behavior will result in specific outcomes.
- *Self-efficacy* (η_3) - perceived ability to engage in a target behavior.
- *Behavior* (η_4) - target action of interest.
- *Behavioral outcomes* (η_5) - results of target behavior, e.g., weight loss due to increased physical activity.
- *Cue to action* (η_6) - trigger to engage in a behavior.
- *Skills training* (ξ_1) - activities that alter an individual's self-management abilities.
- *Observed behavior* (ξ_2) - learning resulting from observing the results of others' behaviors.
- *Perceived social support* (ξ_3).
- *Cues to action* (ξ_4, ξ_8) - internal and external triggers, respectively, that influence engagement in a behavior.
- *Perceived obstacles* (ξ_5).
- *Intrapersonal states* (ξ_6) - physical, mental, and emotional states that influence self-efficacy.
- *Environmental context* (ξ_7).

Dynamical systems models describing behavior change via an SCT-based mechanism stem from a connection to production-inventory systems [1], [4], [9]: Fig. 1 depicts SCT in terms of a *fluid analogy* [1]. Here, the five outputs, $\eta_{1...6}$, are represented as fluid inventories (tanks), which accept inflow streams of fluid. The manner in which the level of fluid in an inventory changes in response to changes in inflows represents the way in which *Self-efficacy*, *Behavior*, etc., respond to changes in the respective factors that influence them. The specific inflows to each individual inventory depicted in Fig. 1 reflect the relationships that formally define SCT (see [10]). For example, the *Self-management skills* inventory (η_1) accepts three inflow streams: *Skills training* (ξ_1), which is an external input to the overall

system and is represented as an exogenous input stream flowing at a known and controlled rate; a portion of the outflow stream from the *Behavior* inventory, which reflects the inter-relationship between the *Self-management skills* and *Behavior constructs*; and the disturbance input ζ_1 , which represents the unmodeled factors that influence *Self-management skills*. Altogether, the six inventories in Fig. 1 are inter-connected to reflect the triadic reciprocity proposed in [10].

An engineering model of SCT is developed by applying the conservation of mass principle (which is used as a general accounting principle here) to the inventories and assuming the dynamic response of each output to changes in inputs are adequately represented by first order differential equations. The result is a system of differential equations:

$$\tau_1 \frac{d\eta_1}{dt} = \gamma_{11}\xi_1(t) + \beta_{14}\eta_4(t) - \eta_1(t) + \zeta_1(t) \quad (1)$$

$$\tau_2 \frac{d\eta_2}{dt} = \gamma_{22}\xi_2(t) + \beta_{21}\eta_1(t) + \beta_{25}\eta_5(t) - \eta_2(t) + \zeta_2(t) \quad (2)$$

$$\tau_3 \frac{d\eta_3}{dt} = \gamma_{32}\xi_2(t) + \gamma_{33}\xi_3(t) - \gamma_{35}\xi_5(t) + \gamma_{36}\xi_6(t) + \beta_{31}\eta_1(t) + \beta_{34}\eta_4(t) - \eta_3(t) + \zeta_3(t) \quad (3)$$

$$\tau_4 \frac{d\eta_4}{dt} = \beta_{42}\eta_2(t) + \beta_{43}\eta_3(t) + \beta_{46}\eta_6(t) + \beta_{45}\eta_5(t) - \eta_4(t) + \zeta_4(t) \quad (4)$$

$$\tau_5 \frac{d\eta_5}{dt} = \gamma_{57}\xi_7(t) + \beta_{54}\eta_4(t) - \eta_5(t) + \zeta_5(t) \quad (5)$$

$$\tau_6 \frac{d\eta_6}{dt} = \gamma_{64}\xi_4(t) + \gamma_{68}\xi_8(t) - \eta_6(t) + \zeta_6(t) \quad (6)$$

where the left hand side of the equations are transition terms (units of η), i.e., the change in the level of an inventory ($d\eta$ [units of η]) over some time (dt [units of time]), is related to the speed at which the inventory level responds to a unit change in the tank's inflows and outflows (time constant, τ); η_i and ξ_i are the output and input variables, respectively, that are fundamental to SCT; γ_{ij} is the gain between input variable ξ_i and output variable η_j ; β_{mn} is the gain for the interrelationship between variable ξ_m and ξ_n ; and ζ_i is an unmodeled disturbance that affects output η_i [1].

SCT is among the most influential theories in behavioral science, and has been recently examined in the context of a physical activity intervention [1]. Specifically, estimated dynamic models were obtained using averaged ILD from six participants in the Mobile Interventions for Lifestyle Exercise and Eating at Stanford (MILES) study [12]. These models focused on a two-input, two-output problem: *Self-efficacy*, as recorded on a 1-11 point scale by participants via smart phone, and *Behavior*, the total number of steps taken

per day as measured by an accelerometer, were the outputs of interest. The two inputs were intervention components: *Skills training*, consisting of tips for engaging in a target behavior delivered as reading material via the ‘mtrack’ smart phone application (recorded as seconds spent reading the tips), and *external cues*, consisting of smart phone reminders to set new physical activity goals (recorded as the number of reminders sent to a participant in a given period of time) [1], [12].

For model estimation, Eqs. (1) through (6) were substituted, rearranged, and transformed to give a state-space representation of the two-input, two-output problem. From this semi-physical structure, a prediction-error estimation approach (the `idgrey` command in MATLAB, which allows a user to specify a state-space model structure in which only certain elements of the matrices are estimated [8]) and the MILES data, the following parameter estimates were obtained:

$$\begin{aligned}\tau_{\{1,2,3,4,5,6\}} &= \{0.66, 2.25, 0.55, 3.00, 0.94, 0.64\} \\ \gamma_{\{11,22,32,33,35,36,57,64,68\}} &= \{1.32, 1, 1, 1, 1, 1, 1, 0.1, 0.88\} \\ \beta_{\{21,31,42,43,54,34,25,14,46,45\}} &= \{0.9, 0.05, 0.9, 0.5, 0.67, 0.18, 0.5, 0.65, 0.01, 0.1\}\end{aligned}$$

Depicted in Fig. 2, these estimates together correspond to model fits—determined using a normalized root mean square error calculation [8]—equal to 49.54% for *Self-Efficacy* and 34.95% for *Behavior* (where 100% would indicate the model explains all of the variance observed in the data) [1]. Because these estimates and fit percentages were obtained in secondary analysis of data with limited construct measurements and for a small number of individuals, these percentages and the model predictions in Fig. 2 are encouraging; a more informative data set will likely further elucidate the role of SCT in physical activity behavior change, i.e., result in better predictive ability and fit percentages.

III. Case Study II: Mediation & Smoking Cessation

Statistical mediation considers a multivariate relationship in which the level of an outcome variable, Y , is determined by the level of an independent variable, X , and a mediator variable, M , where the level of M is also affected by X . Behavioral scientists typically model mediation with the following static structural equations:

$$M = \beta_{01} + aX + e_1 \quad (7)$$

$$Y = \beta_{02} + c'X + bM + e_2 \quad (8)$$

where β_{01} and β_{02} are intercepts, e_1 and e_2 are error terms, and a , b , and c' quantify the net effect X has on M , M on Y , and X directly on Y , respectively [11]; in dynamical systems terms, a , b , and c' are the steady-state gains [5].

Considering X , M , and Y as continuous-time constructs (i.e., X, M , and $Y = f(t)$), each relationship in (7) and (8) can be examined as individual input-output processes. Developed

in detail in [5], dynamical systems models describing a process of behavior change according to a mediational mechanism are represented in algebraic form via Laplace-transform as:

$$M(s) = P_a(s)X(s) \quad (9)$$

$$Y(s) = P_c(s)X(s) + P_b(s)M(s) \quad (11)$$

where P_a , P_b , and P_c represent the individual processes by which changes in $X(t)$ lead to changes over time in $M(t)$, changes in $M(t)$ lead to changes in $Y(t)$, and changes in $X(t)$ lead directly to changes in $Y(t)$, respectively. With the appropriate ILD, $P_a(s)$, $P_b(s)$, and $P_c(s)$ transfer functions can be estimated to describe mediated behavior change.

A University of Wisconsin study collected such ILD. Fig. 3 depicts group average ILD (dash-dot red) for *Craving* (average craving level reported by participants on a given day) and *CPD* (total number of cigarettes smoked per day), collected nightly via personal digital assistant from approximately 100 subjects who received no active cessation therapy from two weeks pre-target quit date (pre-TQD) through the first four weeks of a quit attempt [13]. Using this data, a set of transfer function models were estimated to examine *Craving*-mediated cessation in which *Quit(t)* is treated as $X(t)$, reflecting initiation of a quit attempt ($Quit = 0, t < \text{TQD}$, $= 1, t \geq \text{TQD}$), group average *Craving(t)* ILD is $M(t)$, and group average *CPD(t)* ILD is $Y(t)$. The pem command in MATLAB (a prediction-error approach using sophisticated regression routines that fit a user-specified, low order, continuous-time differential equation to discrete-time data [7], [8]) was used to estimate the parameters in a two step procedure: first, $P_a(s)$ was estimated as a single-input, single-output problem, with *Quit* as the input and *Craving* as the output; next, $P_b(s)$ and $P_c(s)$ were estimated simultaneously in a two-input, one-output problem with *Craving* and *Quit* as the inputs and *CPD* as the output. This resulted in the following estimated transfer functions:

$$P_a(s) = \frac{-3.90(-24.21s+1)}{17.13s+1} \quad P_b(s) = \frac{-0.30}{1.89s+1} \quad P_c(s) = -10.24 \quad (11)$$

As indicated by the quit attempt simulated using these models (dotted brown in Fig. 3) and the 64.7% fit for *Craving* and 84.38% fit for *CPD*, these models quantify the mediational relationship hypothesized to be at play within smoking cessation behavior change. Examining these equations suggest the direct $X(t) \rightarrow Y(t)$ path models the immediate reduction in *CPD* that occurs on TQD, while the $X(t) \rightarrow M(t) \rightarrow Y(t)$ path—i.e., P_a and P_b in series—models the small and slow resumption of smoking post-TQD. The parameter estimates also reflect the inverse response in *Craving* (initial increase before ultimately settling to reduced levels, reflected in the negative P_a gain and zero term values), the fast reduction in smoking on TQD (there are no time constants or derivative terms required by P_c), and the small resumption in smoking (small P_b gain, equal to -0.30) [5].

IV. Summary & Future Work

The case studies presented in this paper illustrate the potential of a dynamical systems approach for describing theorized behavior change mechanisms. Specifically, stemming from a connection between production-inventory management in supply chains [4], [9], differential equation models were presented that leverage ILD to describe behavior change according to SCT and mediational processes in the context of a physical activity intervention and smoking cessation. While promising, both of the case studies presented entail secondary analysis of existing data, which were not obtained through experiments designed with dynamical systems modeling in mind. In the future, high fidelity models with greater predictive ability could be estimated using more informative data collected through novel trials that are better suited for this analytical approach. Notably, experiment-design principles from system identification could be used to develop novel input signals [1], [4]. For these experiments, the value of the adjustable input signal of interest would be varied over time such that the input signal is more *persistently excited* in order to promote a greater range of dynamics and variability in the outputs [7]. As the processes examined in these experiments involve human subjects, these protocols must adhere to strict practical, ethical, and medical constraints. For example, [4] describes a “patient-friendly” clinical trial protocol which varies the dose of a pharmaceutical for a pain-management intervention on a biweekly basis, and repeats the dose schedule so that the first set of measurements can be used for estimation and the second set for validation. Ultimately, more rigorous estimation and validation of dynamical systems models should draw from data obtained in such novel clinical trials in order to more reliably quantify the dynamics of SCT and mediational processes.

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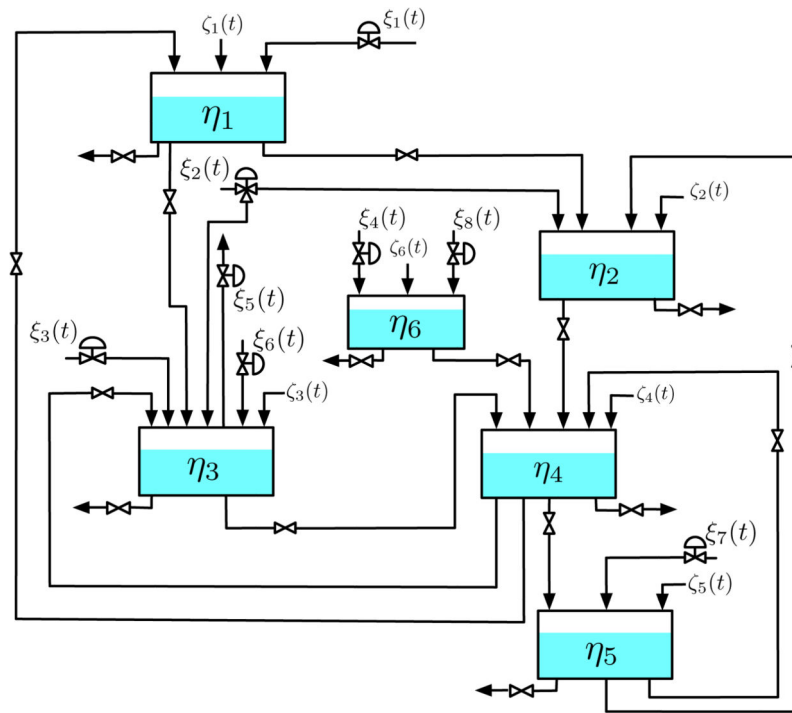


Fig. 1. Fluid analogy describing behavior change according to the mechanism constituting SCT.

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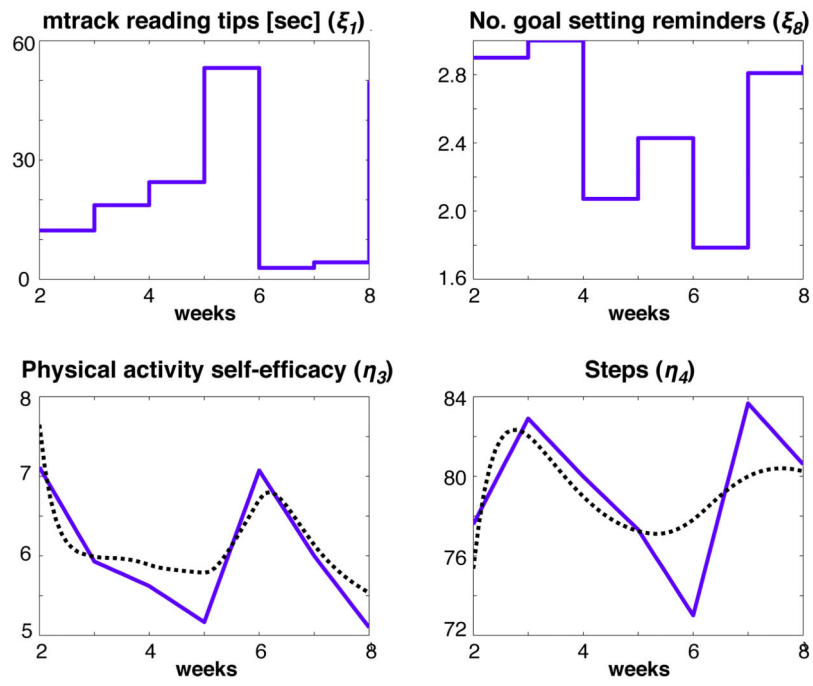


Fig. 2. Average data (solid blue) used for estimation of the two-input, two-output SCT problem and the resulting model predictions (dotted black).

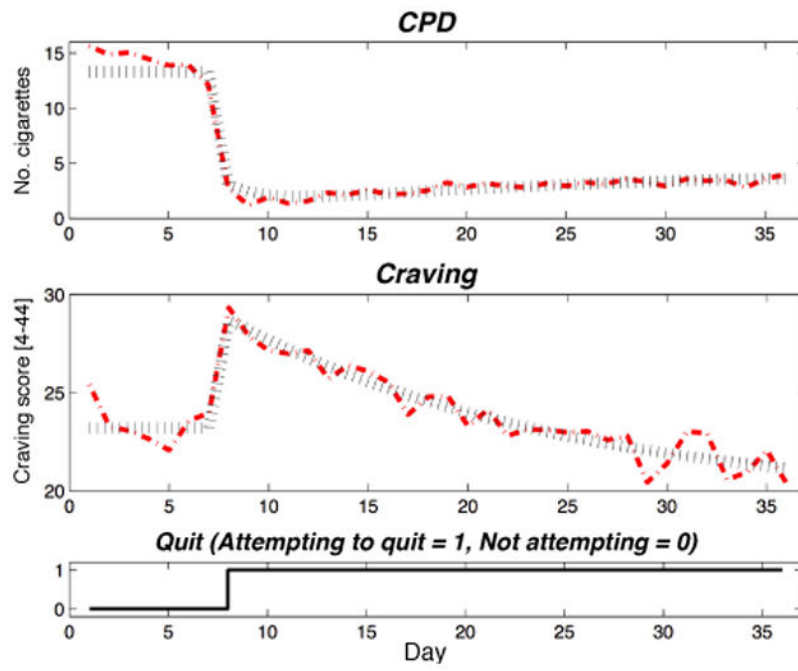


Fig. 3. Averaged *Craving* and *CPD* ILD (dash-dot red) used to model *Craving*-mediated changes in *CPD* during a quit attempt; model predictions depicted as dotted brown lines.