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A Dynamical Systems Model of Social Cognitive Theory

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***Abstract*— Social Cognitive Theory (SCT) is among the most influential theories of health behavior and has been used as the conceptual basis of interventions for smoking cessation, weight management, and other related health outcomes. SCT and other related theories were developed primarily to explain differences between individuals, but explanatory theories of within-person behavioral variability are increasingly needed to support new technology-driven interventions that can adapt over time for each person. This paper describes a dynamical system model of SCT using a fluid analogy scheme. A series of simulations were performed to explore and better understand SCT. The model incorporates a nonlinear feature called habituation, an important feature of behavioral response resulting from continuous stimulus. It also illustrates how control systems engineering principles provide a promising approach for advancing health behavior theory development, and for guiding the design of more potent and efficient effective interventions.**

I. INTRODUCTION

Control system engineering principles have been applied to diverse fields. One key advantage of using this representation of systems is its capability of supporting the design of model-based controllers that can manipulate the magnitude and shape of the system response to accomplish a desired goal.

The behavioral sciences have traditionally utilized three broad methods of scientific inquiry to identify behavior change strategies including highly-controlled laboratory-based experiments, epidemiologic correlational studies, and randomized controlled trials [1]. New and emerging technologies have opened new avenues for gathering a much wider realm of data (e.g. mobile-phone based sensing) and for intervening upon behavior in context via mobile technologies [1]. These new data streams and intervention mechanisms have surpassed most behavioral theories in their ability to provide insights about "just-in-time" feedback and interventions [2]. Since health behavior makes use of theories to guide the research to prevent or treat diseases, promote health, and/or enhance wellbeing [3], new methods are needed that can take advantage of these new data streams to support behavioral interventions. Given these important advances, the following questions are considered: Are dynamical systems capable of depicting human behavior? Can controllers designed on the basis of control engineering principles, be useful for behavioral interventions?

Some significant efforts have been made to integrate control systems principles into health behavior. In the work of Rivera, Pew and Collins [4] a procedure to design an adaptive behavioral intervention based on control principles was proposed. Also a dynamical systems model for the Theory of Planned Behavior (TPB) [5], an influential behavioral theory, and its applications for improvements on gestational weight gain interventions [6] have been presented.

As highlighted above, behavioral theory plays a central role in the creation of behavior change strategies and thus the choice of behavioral theories is important. While there are known limitations with many behavioral theories [2], [7], Social Cognitive Theory (SCT) is among the most influential and has been used to guide many health behavior interventions [8]. Health behavior theories such as SCT are essentially models of the influences on behavior and their interrelationships, and they are amenable to various modeling techniques. Robust computational modeling approaches would provide a more flexible and rigorous test of SCT and other health behavior theories that could serve to confirm, revise, or refute SCT and other theories [9]. Further, computational models can aid in better specifying contextually relevant and instantaneous interrelationships that can now be measured continuously over time.

Behavioral response habituation as a result of repeated stimulation [10] is a well-known phenomenon that can be observed in many behavioral situations. While SCT does not specify this, behavioral responses to an external stimulus would seem to follow the principles of habituation. Considered one of the simplest forms of learning, habituation is actually quite complex and covers many processes [11] including: spontaneous recovery of the response when the stimulus is withheld, more rapid habituation following prior series of habituation and recovery, effects of frequency, among others. Some of these basic habituation processes have been modeled from a machine learning perspective [12].

The purpose of this paper is to propose a dynamical systems model for Social Cognitive Theory based on descriptions of SCT constructs and interrelationships [13], and to perform simulations of the model using physical activity of individuals over time as a referential behavior. The model features a nonlinear structure that addresses the problem

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of habituation. A subsection of the model is reconciled to actual data from MILES [14], a lifestyle intervention focused on physical activity. Based on the available data, for the remainder of the paper we will utilize physical activity as a primary example behavior but the model and constructs can be used for other behaviors. The proposed model can ultimately serve a role as the controller model in a “just-in-time” adaptive intervention using MPC [15].

This paper is organized as follows. Section II presents a description of SCT and its constructs. Section III describes the development of the fluid analogy. Section IV presents how the model was constructed including assumptions and how habituation was represented. Section V discusses simulation results for a hypothetical case study. Section VI contrasts experimental data MILES against simulations. Section VII gives a summary of our conclusions and future work.

II. Social Cognitive Theory

SCT describes a human agency model in which individuals proactively self-reflect, self-regulate, and self-organize [16]. Core to this is the concept of triadic reciprocity in which personal factors (cognitions, affect, biology), environment, and behavior all co-interact and influence one another. SCT estimates the ability of an individual to engage in a targeted behavior, based on internal and external parameters and their interrelationships, with some self-perceived and others externally measured.

The following SCT components are generated as a consequence of variation of external or internal stimuli. From the engineering point of view these might be considered as outputs; these components are:

- *Self-efficacy*, which is the perceived confidence in one’s ability to perform a target behavior. It is an essential factor that influences behavior and that is influenced by behavior and the environment.
- *Outcome expectancies*, the perceived likelihood that performing a target behavior will result in specific, anticipated outcome. It is also a central personal factors component.
- *Behavioral outcomes*, the outcomes obtained as a result of the behavior. These are directly related to outcome expectancies and the future behavior.
- *Self-management skills*, this set of skills involves a class of complex behaviors such as self-monitoring, goal setting, self-reinforcement, stimulus control etc, by which the individual increases the potential success for a target behavior.
- *Behavior*, the action of interest. For example, it could correspond to a metric of physical activity (e.g. daily steps, minutes spent in daily moderate intensity physical activity) or involvement with an addictive substance (e.g. cigarettes per day or alcoholic drinks per day).

According to the theory, there are variables that act as stimuli to promote (or relegate) behavior and the components. These can be considered inputs to the system, and can be external or internal to the individual. They are:

- *Skills training*. These activities help to increase (or decrease) self-management skills.
- *Observed behavior (vicarious learning)*, it influences both self-efficacy and outcome expectancies as the individual observes the result of the others performing the behavior.
- *Perceived social support and verbal persuasion*, can influence self-efficacy, an example is the availability of others who are willing to engage in physical activity or who support increased physical activity.
- *Perceived barriers and obstacles*, are external conditions that affect behavior, for example physical activity can be reduced because of insufficient time, and/or bad weather for outside activity.
- *Intrapersonal states*, consist of an array of physical, mental, and emotional states of the individual that influence self-efficacy. There are both positive and negative emotional states like happiness or sadness.
- *Environmental context* in which the behavior occurs, influences directly the resultant behavioral outcomes.
- *Internal and external cues to action*, directly influence behavior. In SCT, beliefs (e.g., self-efficacy) are conceptualized as predispositions for engaging in a behavior that is then triggered by a *cue to action*.

III. Fluid Analogy

The proposed fluid analogy of SCT is presented in Fig. 1. It depicts how the various components relate with one another over time, particularly to understand behavior. Main constructs are treated as inventories; other components and properties are depicted as inflows and/or outflows. This model was developed based on a daily time-frame; similar models with more or less granular time-frames could be adapted depending on the behavior and time frame of interest.

In the schematic, behavior (η_4) is represented as a fluid inventory that increases and decreases in frequency and/or duration over time. Self-efficacy (SE) (η_3), is represented as an inventory of varying levels that differs not only between individuals and specific behaviors but also fluctuates within an individual. The following are the SCT factors that are theorized to increase or decrease the SE inventory.

1) Perceived barriers and obstacles (ξ_5) to engaging in a behavior deplete self-efficacy (SE).
2) Perceived social support and verbal persuasion increase the inventory of SE (ξ_3).
3) Observed behavior (ξ_2) increases SE.
4) Intra-personal states (ξ_6) either add or deplete the inventory of self-efficacy (SE).
5) Prior experience engaging in the behavior (β_{34}) is a critical learning feedback loop that adds or depletes SE to subsequently engage in the behavior.
6) Self-management skills (η_1) influences self-efficacy.

Behaviors are inherently followed by positive and/or negative consequences, some proximal and some distal, or lack of consequences. For example, engaging in physical activity could result, short term, in feeling fatigued or invigorated.

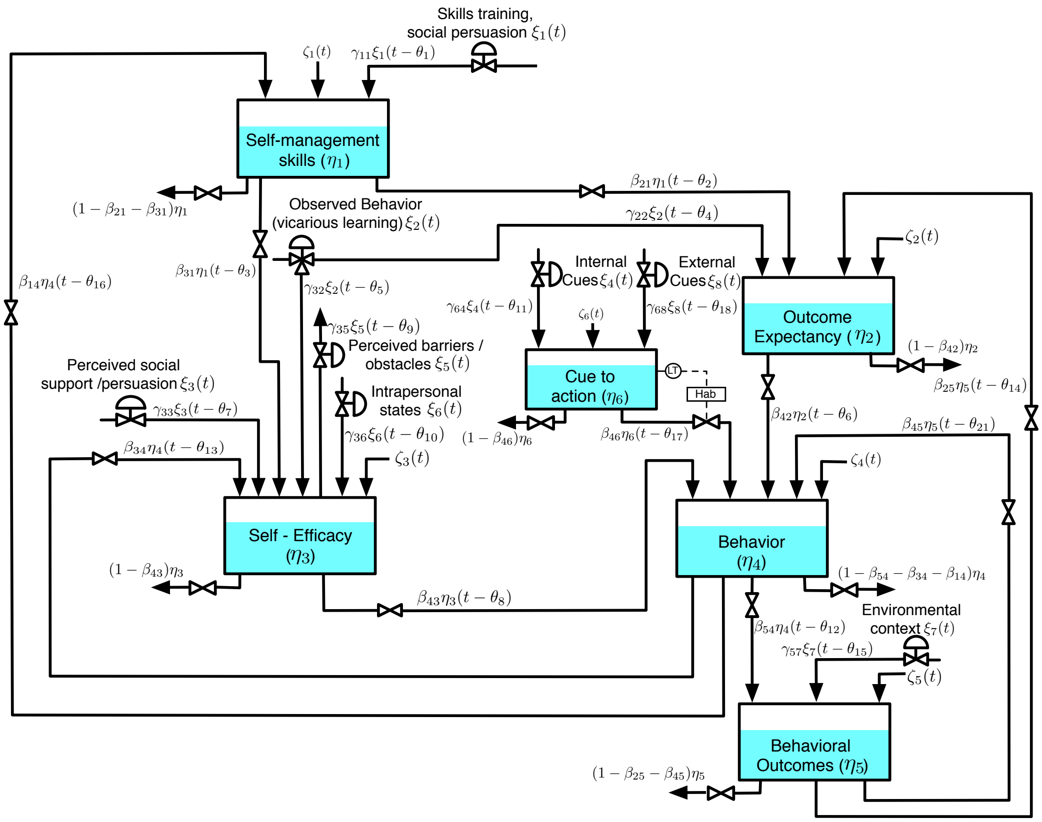

Fig. 1. Fluid analogy for Social Cognitive Theory augmented with habituation.

Social reinforcement may ensue from engaging in physical activity. Over the longer-term, physical activity may lead to improved health, or conversely injury. These behavioral outcomes (η_5) produce a feedback loop to outcome expectancies (η_2) through β_{25} in which positive outcomes increase outcome expectancies and negative do the opposite. As was noted before, behavioral outcomes are influenced by the environmental context (ξ_7). Observing the consequences of the behavior experienced by others (ξ_2) adds or depletes the outcome expectancy inventory. Also, self-regulatory skills influence outcome expectancies (β_{21}).

Finally, cue to action (η_6) directly influences behavior. Given the daily time-frame of this model, however, we have treated η_6 as an inventory that represents the various cues to action that accumulate during the day. These cues can be external (e.g. friend asks you to take a walk) or internal (e.g. getting tired or stiff from sitting). They can occur naturally (e.g. good weather) or artificially (e.g. reminder). To complete the fluid analogy model, disturbances (ζ) have been added. Disturbances are any uncontrolled factors that influence the inventories.

IV. Dynamical Model Description

To obtain a mathematical model, it is necessary to describe how the inventories and their respective inflows and outflows fit within a dynamical system. This process was described by Navarro Barrientos, Rivera and Collins in a dynamic model for the Theory of Planned Behavior [5].

Six inventories are considered in the diagram represented by the variables η_1,..,η_6. The eight exogenous inputs are are represented by ξ_1,..,ξ_8. From each inventory there are a number of inflow resistances represented by the coefficients γ_{11},..,γ_{68}, and outflow resistances represented by β_{21},..,β_{46}. One way to think about these resistances is that they can be considered the fraction of each inventory or input that leaves the previous instance and then feeds the next inventory.

There are other parameters that represent the physical characteristics of each inventory and flow; they have an important effect on the dynamic behavior of the system. First we have time constants τ_1,..,τ_6 that represent the capacity and allow for exponential decay (or growth) of the inventory, also time delays (θ_1,..,θ_{18}) for each flow signal are used. Unmeasured disturbances (which may reflect unmodeled dynamics) are also considered as ζ_1,..,ζ_6.

A. Differential equation representation

An assumption of the principle of conservation of mass was used within a fluid analogy such that the sum of all the inflows minus all the outflows results in an accumulation term denoted by the time constant τ times the rate of change (derivative) in the level of the inventory. The following equations define the system for each tank:

$$\tau_1 \frac{d\eta_1}{dt} = \gamma_{11}\xi_1(t-\theta_1) + \beta_{14}\eta_4(t-\theta_{16}) - \eta_1(t) + \zeta_1(t) \quad (1)$$

$$\tau_2 \frac{d\eta_2}{dt} = \gamma_{22}\xi_2(t-\theta_4) + \beta_{21}\eta_1(t-\theta_2) + \beta_{25}\eta_5(t-\theta_{14}) - \eta_2(t) + \zeta_2(t) \tag{2}$$

$$\tau_3 \frac{d\eta_3}{dt} = \gamma_{32}\xi_2(t-\theta_5) + \gamma_{33}\xi_3(t-\theta_7) - \gamma_{35}\xi_5(t-\theta_9) + \gamma_{36}\xi_6(t-\theta_{10}) + \beta_{31}\eta_1(t-\theta_3) + \beta_{34}\eta_4(t-\theta_{13}) - \eta_3(t) + \zeta_3(t) \tag{3}$$

$$\tau_4 \frac{d\eta_4}{dt} = \beta_{42}\eta_2(t-\theta_6) + \beta_{43}\eta_3(t-\theta_8) + \beta_{46}\eta_6(t-\theta_{17}) + \beta_{45}\eta_5(t-\theta_{21}) - \eta_4(t) + \zeta_4(t) \tag{4}$$

$$\tau_5 \frac{d\eta_5}{dt} = \gamma_{57}\xi_7(t-\theta_{15}) + \beta_{54}\eta_4(t-\theta_{12}) - \eta_5(t) + \zeta_5(t) \tag{5}$$

$$\tau_6 \frac{d\eta_6}{dt} = \gamma_{64}\xi_4(t-\theta_{11}) + \gamma_{68}\xi_8(t-\theta_{18}) - \eta_6(t) + \zeta_6(t) \tag{6}$$

The system includes first-order differential equations, but to describe a more elaborate transient response (such as overdamped, critically damped or underdamped responses), a second order system could be used. This would lead to an extension of the fluid analogy which includes a self-regulatory controller for each inventory, as is described in Navarro-Barrientos *et al.* [5].

B. Model considerations

The following assumptions were made:

- The sum of all the outflows must add up to the value of the respective inventory, so an outflow of $(1-\beta_{ij}-...-\beta_{kl})$ was included, therefore the following constraints must be satisfied:

$$\beta_{21}+\beta_{31} \leq 1 \quad \beta_{42} \leq 1 \quad \beta_{43} \leq 1$$
$$\beta_{54}+\beta_{34}+\beta_{14} \leq 1 \quad \beta_{25}+\beta_{45} \leq 1 \quad \beta_{46} \leq 1$$

- The initial level of the inventories were determined by solving the system of equations at steady state.
- The time unit is days.
- All the inventories have values within 0 and 100 %.
- All the time delays will be considered to be zero; this is for simplicity and clearness of the results.
- Uncertainties are zero mean stochastic signals.
- The signals intrapersonal states (ξ_6) and environmental context (ξ_7) are considered as auto-correlated noise.

C. Nonlinear dynamics of habituation within the SCT model

Habituation, which was defined above, usually follows a negative exponential curve. Marsland [12] proposed different methods for modeling some of the basic characteristics of habituation in the perspective of learning systems using first order derivatives to depict exponential decays. Since our purpose is to model SCT and habituation in the same structure, a nonlinear consideration will be used to represent both within the same system but with a parameter varying strategy. For simplicity we will focus only on the following common characteristics of habituation [11]:

- Repeated application of the stimulus resulting in a progressive decreased response.
- If the stimulus is withheld, the response recovers at least partially over time.
- More frequent stimulation results in more rapid and/or more pronounced response decrement.

It is possible to obtain more complex models that represent other habituation characteristics, but these models will depend on the inputs of the particular behavioral situation.

In our linear model if the stimulus (e.g. internal cue ξ_4) is continually or repeatedly applied, the response (behavior η_4) will grow until it reaches its maximum value, and it will stay there. The inventory cue to action (η_6) can be thought as an accumulation of the different cues such that it is dependent of the magnitude and frequency of the received stimuli. This value is used to modify the parameter β_{46} that represents the effect of cue to action (η_6) over behavior (η_4).

As an example of a gain schedule for physical activity, we will consider the regular (linear) value of β_{46} as 0.44. If cue to action (η_6) surpass the level of 90% , β_{46} is adjusted to 0.4 representing a reduction on the increase rate of behavior due to the effect of repeated cues. If η_6 keeps increasing (greater than 95%), then β_{46} is fixed to zero, meaning no further increases in behavior and that it will start to decrease to its original value. This gain schedule is suitable for a physical activity example, but for other situations different analysis must be developed.

V. Simulations

The simulations were designed to represent the amount of physical activity performed by an individual during a period of 20 days, the model parameters were chosen as well based on the type of behavior. Some scenarios are depicted showing the dynamic response of the system to different variations on its inputs, all considering the following parameter values:

- $\tau_1 = 1, \tau_2 = 1, \tau_3 = 1, \tau_4 = 2, \tau_5 = 1, \tau_6 = 3$
- $\gamma_{11} = 3, \gamma_{22} = 1, \gamma_{32} = 2, \gamma_{33} = 1, \gamma_{35} = 1, \gamma_{36} = 1, \gamma_{57} = 2, \gamma_{64} = 15, \gamma_{68} = 15$
- $\beta_{21} = 0.3, \beta_{31} = 0.5, \beta_{42} = 0.3, \beta_{43} = 0.8, \beta_{54} = 0.3, \beta_{34} = 0.2, \beta_{25} = 0.3, \beta_{14} = 0.23, \beta_{46} = 0.44, \beta_{45} = 0.1$

The first scenario is depicted in Fig. 2 and illustrates the effect of cue to action in the system under conditions of low self-efficacy. Observed behavior and perceived social support are held at constant low levels ($\xi_2 = \xi_3 = 3$). The input perceived barriers is kept at a high value ($\xi_5 = 10$). Within this context, an external cue occurs starting at day 2 ($\xi_8 = 5$), subsides on day 6-7, recurs on day 8 and then disappears at day 12. The result of the applied signals on the inventories is a small, dampened increase on behavior that subsides when the cue to action is subsequently depleted.

The second scenario, is also shown in Fig. 2, and illustrates an initiation of the behavior and a further maintenance. The external cue to action (ξ_8) has similar values as the previous scenario but within the context of high self-efficacy. Observed behavior and perceived social support are kept at high levels ($\xi_2 = 10, \xi_3 = 10$) and perceived barriers are decreased to a low level ($\xi_5 = 2$). The result is now a considerable increase on the behavior inventory, via an increase in internal

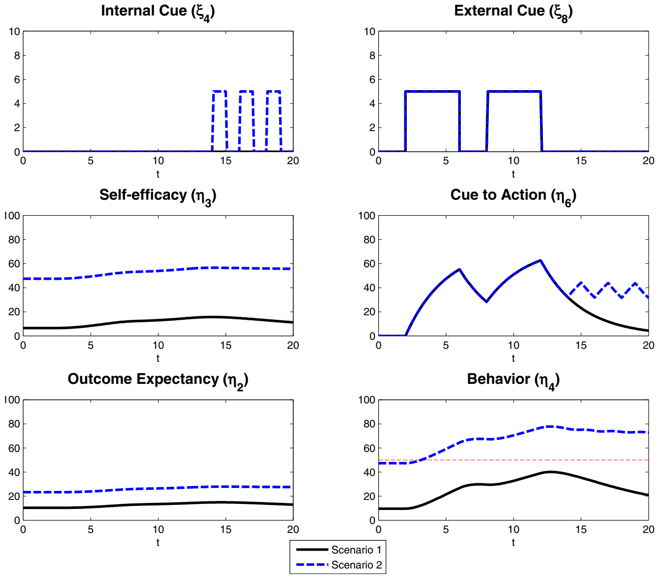

Fig. 2. Scenarios 1 and 2: failure (success) on the initiation of physical activity behavior under low (high) self-efficacy and in the presence of external cues.

cues (example: after few days walking daily at the same time, and one day resting, the individual experiences the internal cue of a desire to walk). The behavior is sustained with fewer external cues but with an increased self-efficacy as a result of the feedback loop between SE and behavior.

The third scenario, showed in Fig. 3, illustrates the effect of habituation. External cue (ξ_8) is shown, the rest of the inputs keep similar values as scenario 2, to allow high self efficacy and the fast engagement in behavior. Behavior (η_4) is depicted for both, a linear case with no habituation, and the proposed model (nonlinear) with the habituation gain schedule. An external cue (ξ_8) is applied from day 1 to day 14, initially the individual responds with a sustained increase on the behavior, but after 7 days it starts to reduce the rate of increase (β_{46} reduced from 0.44 to 0.4) and later begins a decrease in behavior that finally results in a reduction of the activity (β_{46} reduced to 0), returning to the initial value. At day 14 the repeated stimulus (ξ_8) is retired, here we can observe how the behavior partially recovers, as suggested by habituation theory [11].

VI. Comparison with intervention data

In this section we contrast measured data from a physical activity intervention against simulations using our proposed model. The data are taken from a study called Mobile Interventions for Lifestyle Exercise and Eating at Stanford (MILES) [14] focused on behavioral interventions for physical activity in aging adults using mobile phones. The data were from a subset of the full sample; specifically, 68 adults ages 45 years and older who agreed to participate in the experiment with the support of a smartphone during eight weeks. To measure the behavioral variables daily questionnaires [14] were used and gathered via the smartphone.

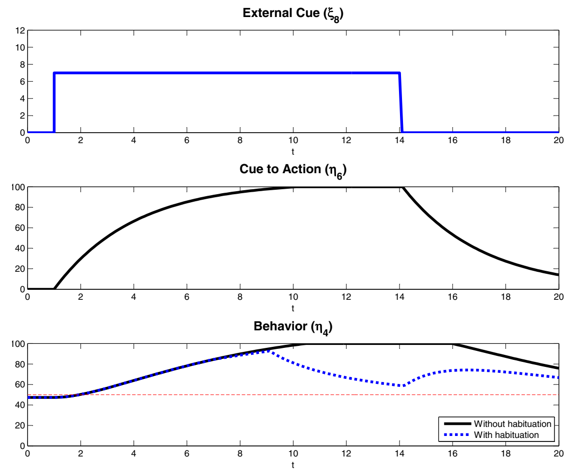

Fig. 3. Scenario 3: Behavior under a persistent external cue that causes habituation, and later recovery after the stimulus is removed. High self-efficacy conditions are considered.

Physical activity (behavior) was measured via a smartphone-based accelerometer.

For comparison purposes we used a smaller subset of participants with complete data, including interactions with the smartphone app features for the rational app [14]. The selected inputs correspond to weekly data for skills training (ξ_1), and external cues (ξ_8), the correspondent outputs are self-efficacy (η_3) and behavior (η_4). For simulation purposes the specified inputs were replicated, and the internal model parameters were estimated via a grey-box system identification procedure [17] in MATLAB that allowed the search of parameters keeping the defined model structure. The estimated values of the model parameters are:

- $\tau_1 = 0.66, \tau_2 = 2.25, \tau_3 = 0.55, \tau_4 = 3, \tau_5 = 0.94,$ $\tau_6 = 0.64$
- $\gamma_{11} = 1.32, \gamma_{22} = 1, \gamma_{32} = 1, \gamma_{33} = 1, \gamma_{35} = 1, \gamma_{36} = 1,$ $\gamma_{57} = 1, \gamma_{64} = 0.1, \gamma_{68} = 0.88$
- $\beta_{21} = 0.9, \beta_{31} = 0.05, \beta_{42} = 0.9, \beta_{43} = 0.5, \beta_{54} = 0.67,$ $\beta_{34} = 0.18, \beta_{25} = 0.5, \beta_{14} = 0.65, \beta_{46} = 0.01, \beta_{45} = 0.1$

The results are shown in Fig. 4 including the MILES data and simulations based on the estimated model. We can observe a similar pattern between the responses from the model and the MILES data. The percentages of fit between the signals are calculated using Equation 7 and they are:

$$\%fit = 100\left(1 - \frac{\|y - \hat{y}\|}{\|y - \text{mean(y)}\|}\right) \tag{7}$$

$$\begin{aligned} \textit{Self-efficacy}(\eta_3) &= 49.54\% \\ \textit{Behavior}(\eta_4) &= 34.95\% \end{aligned}$$

The mismatch between the data and model output can be explained by unmeasured dynamics, disturbances and unknown external signals that, as can be observed in the model, can be present in the other inputs. Since we are dealing with human behavior and in some cases with information collected via questionnaires, this type of mismatch is expected, however

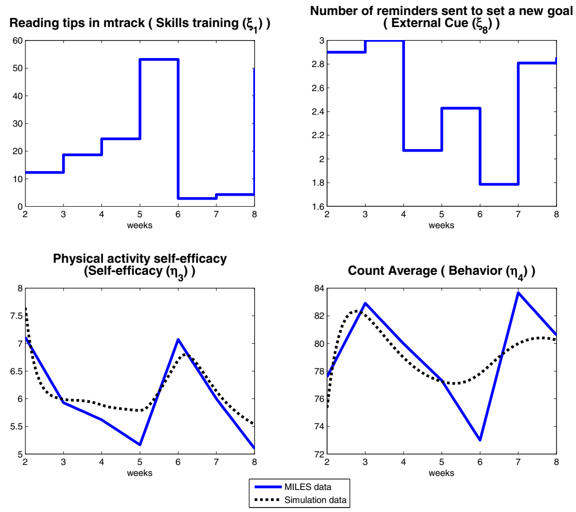

Fig. 4. Data from MILES study (solid line) contrasted against simulation results from the model (dotted line) considering the same input values for both scenarios.

it is observable that the same shape of response could be predicted with the proposed model. For a more complete validation, a new experiment may be designed using more appropriate *a priori* within-person experimental procedures.

VII. Conclusions and Future Work

In this paper we have described how SCT can be represented as a control systems model. It is important to note that the additional theoretical specificity needed to construct this model was based on the authors understanding of SCT. While we strove to be consistent with the theory and existing data on SCT construct relationships, some of the specificity in this model was based not on explicitly stated SCT hypotheses but on the interpretation of the theory by the authors.

The simulations proved to be valuable for better specifying implicit assumptions made within SCT to ensure better operationalization. While simulations provide useful iterative feedback on how the model performs on various scenarios and identifies flaws in the model that produce unrealistic outcomes, testing these models with actual data is critical.

Further studies are being developed to strengthen the application of this model. The model structure must be more deeply validated, via data that can from experiments.

Additional details and approaches involved in the theory, such as overflow of reward structures (behavioral outcomes), could be modeled with more elaborate nonlinear schemes that can improve the accuracy of the model. With the obtained model it is possible to evaluate decision rules that can lead to adaptive behavioral interventions and potentially more potent interventions for health promotion. These can be designed by hybrid model predictive controllers [15].

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