Applying Dynamical Systems Modeling to Time-Intensive Data

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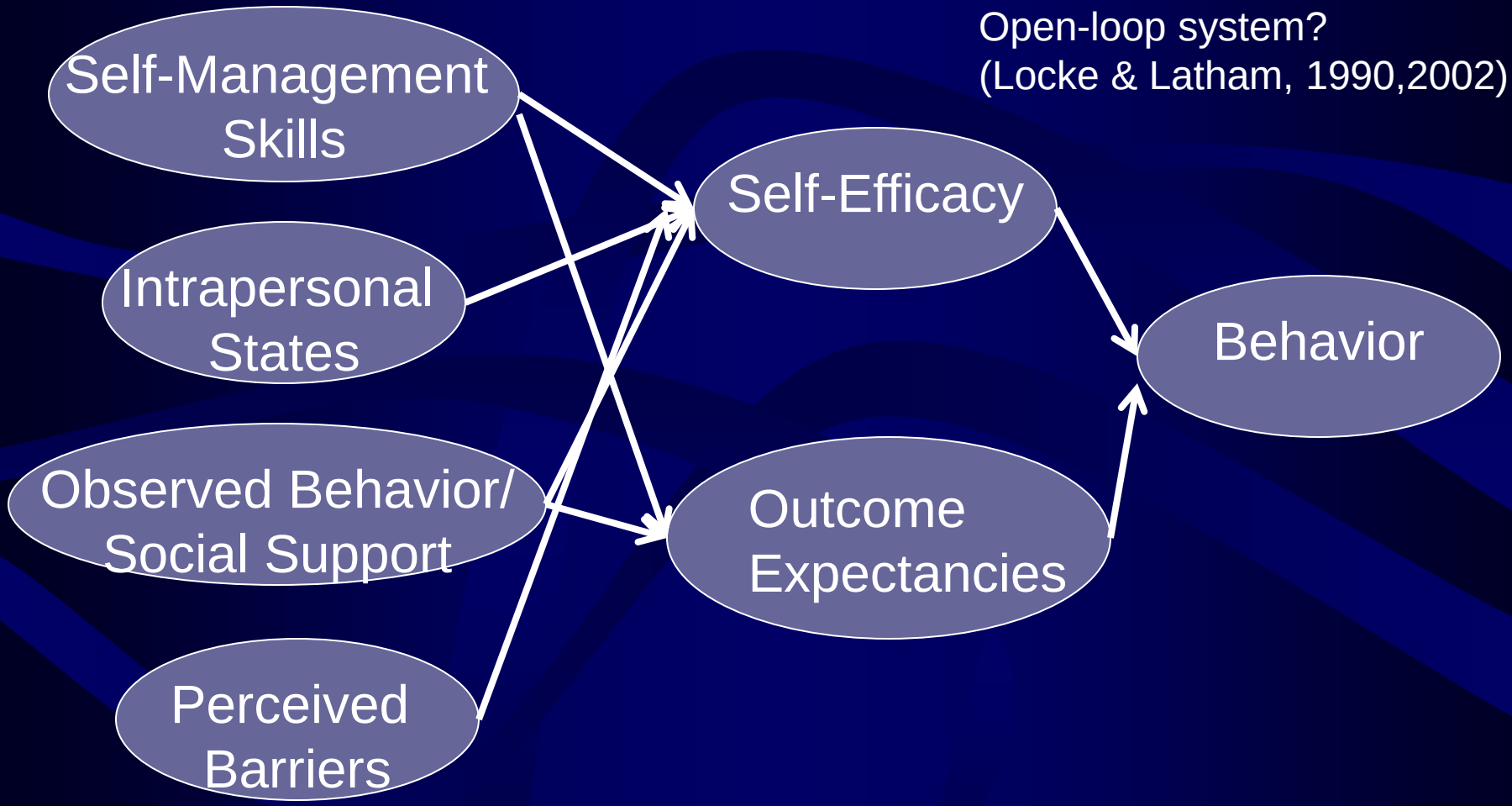
Ecological Momentary Assessment (EMA)

- **Ecological**
  - Real-world environments & experience
  - Provides ecological validity
- **Momentary**
  - Real-time assessment & focus
  - Avoids recall bias
- **Assessment**
  - Self-report
  - Repeated
  - Intensive Longitudinal Data (ILD)
  - **Allows analysis of physiological/ psychological/behavioral processes over time**

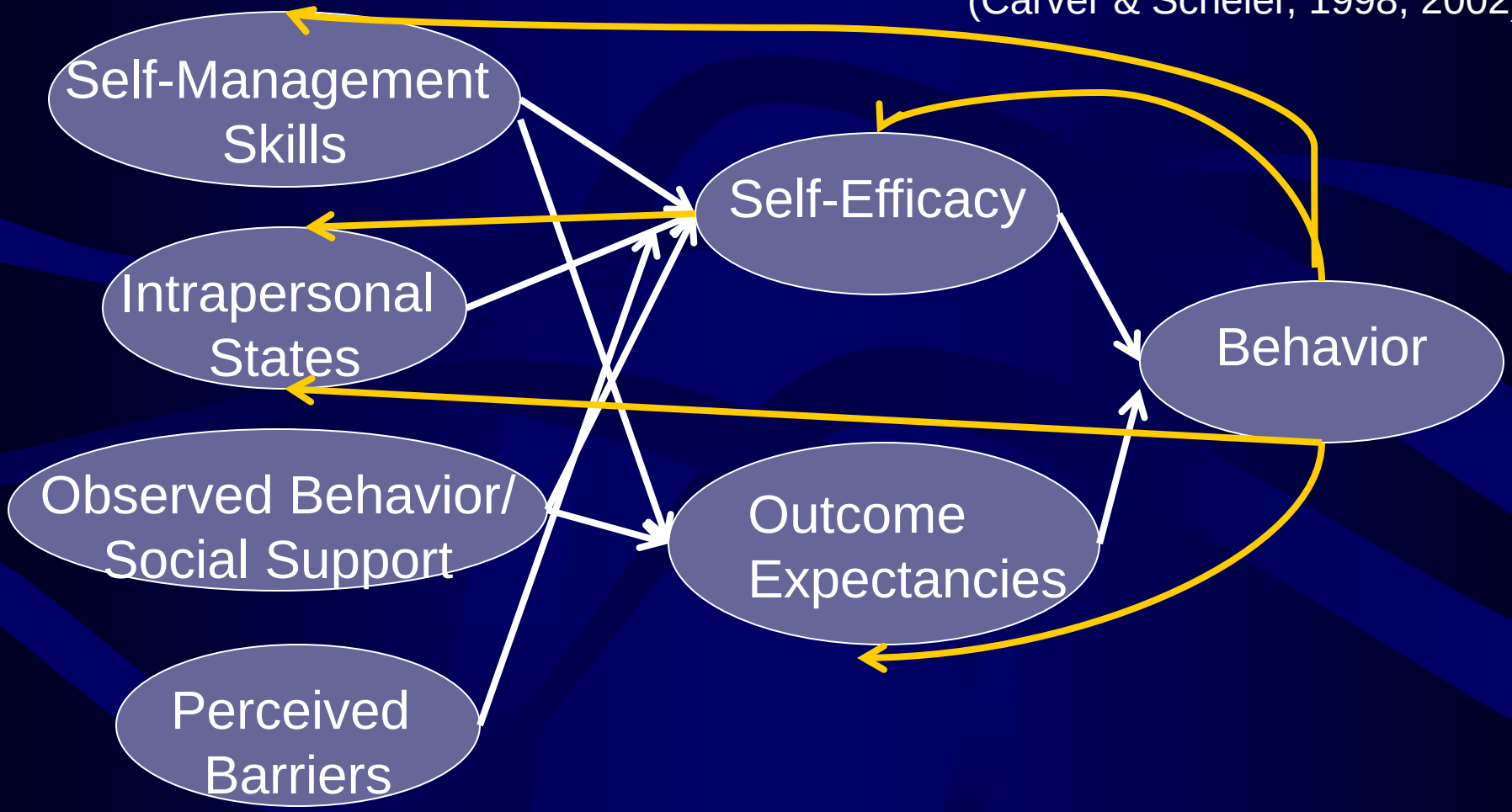
(Stone & Shiffman, 1994)

Social Cognitive Theory (SCT)

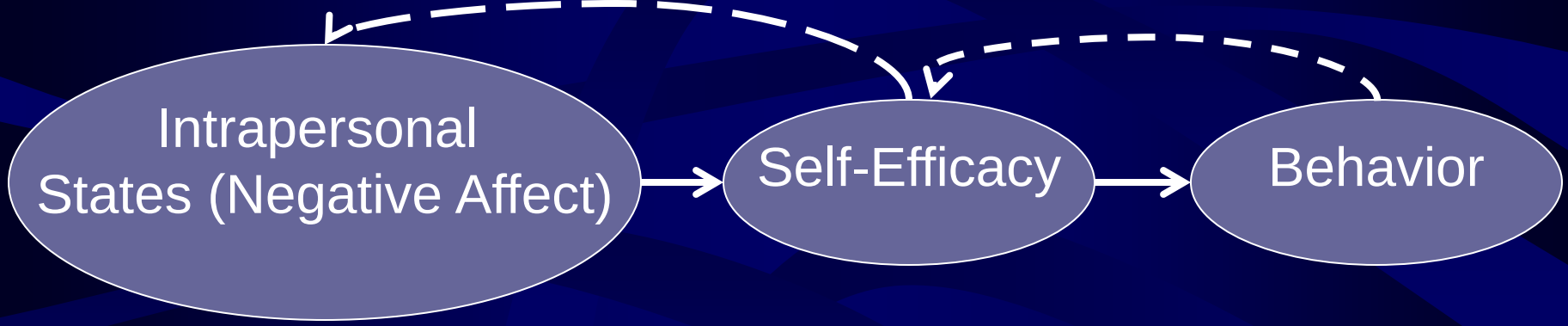


Social Cognitive Theory (SCT)

Closed-loop system?
(Carver & Scheier, 1998, 2002)



Intensive Longitudinal Data (ILD) and Ecological Momentary Assessment (EMA) can yield insights into “closed loop” behavior.


Intrapersonal States (Negative Affect)
Self-Efficacy
Behavior

Traditional EMA Data Analytic Techniques

Multilevel regression modeling

-Adjusts SE's based on clustering of observations within people

-Allows effects to vary across people

-Difficulty with feedback loops, nonlinear effects, and effects that vary dynamically over time

- SAS (PROC Mixed/PROC NL Mixed)
- HLM (Bryk & Raudenbush)
- SPSS (Mixed Models)
- SUDAAN (SEMETHOD=zeger)

Advantages of Dynamical Systems Modeling of EMA Data

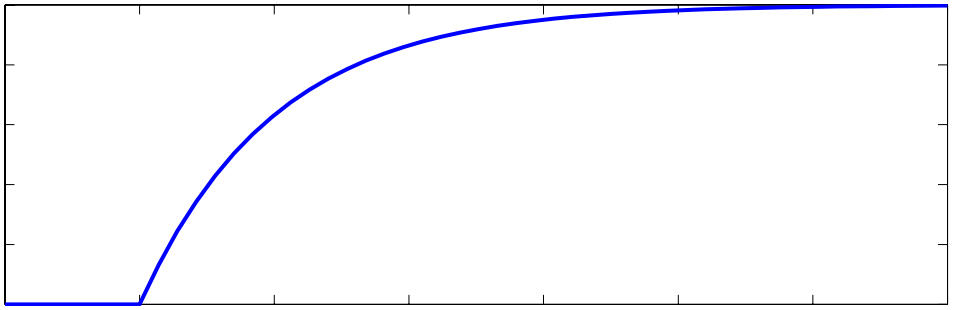
- Better understand the concepts of effect and change in behavioral systems; this includes characterizing *speed, shape, and magnitude of response*, both within and between participants.
- Allows the more efficient use of intensive longitudinal data.
- Ultimately enables the use of control systems engineering principles for achieving just-in-time adaptive interventions.

First-Order System

$$\tau \frac{dy}{dt} + y(t) = K\ u(t)$$

Output *y(t)*
(e.g., Craving, Cigarettes Smoked)

Input *u(t)*
(e.g., Quitting, Dosage Change, Stress)



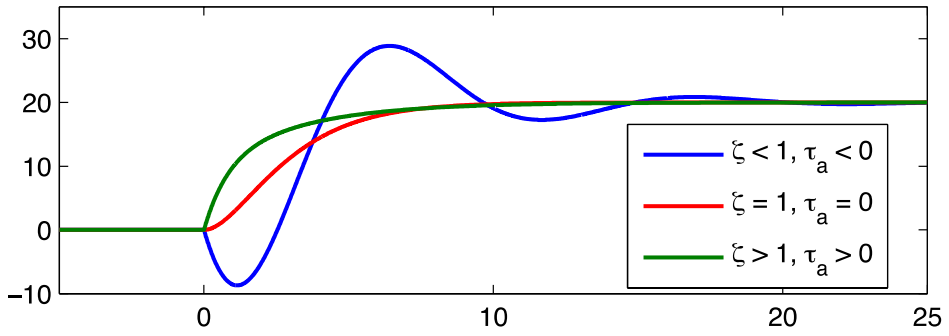
The *gain K* and *time constant tau* reflect magnitude and speed-of-response, respectively.

Second-Order System

$$\tau^2 \frac{d^2y}{dt^2} + 2\zeta\tau \frac{dy}{dt} + y(t) = K_p \left(u(t) + \tau_a \frac{du}{dt} \right)$$

Output *y(t)*
(e.g., Craving, Cigarettes Smoked)

Input *u(t)*
(e.g., Quitting, Dosage Change, Stress)



Second-order systems can display underdamped (oscillatory) behavior and "inverse" response.

- Longitudinal EMA study of the psychological, social, and contextual influences on physical activity
- Low- and middle-income adults living in Southern California
- 3 waves of EMA separated by 6 months each

EMA Procedures

- Loaned mobile phone
- Monitoring occurred across 4 days (Sat.-Tues) for each wave
- Signal-interval contingent hybrid sampling

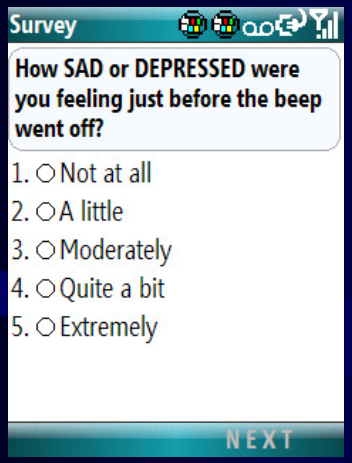
Ecological Momentary Assessment Prompting Schedule

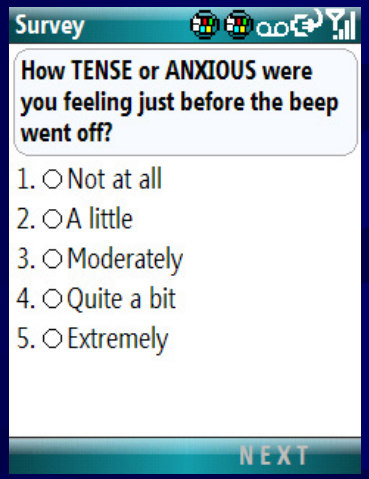
Day	6:30-6:45am	8-10am	10am-12pm	12-2pm	2-4pm	4-6pm	6-8pm	8-10pm
Saturday	X	X	X	X	X	X	X	X
Sunday	X	X	X	X	X	X	X	X
Monday	X	X	X	X	X	X	X	X
Tuesday	X	X	X	X	X	X	X	X

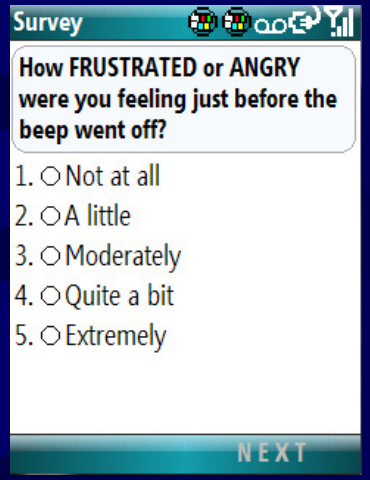
Note: Question sequences are prompted at a random time within each interval.

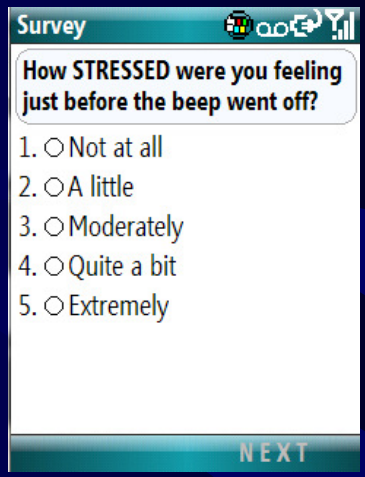
EMA Items

Negative Affect (4 items, α = .87)

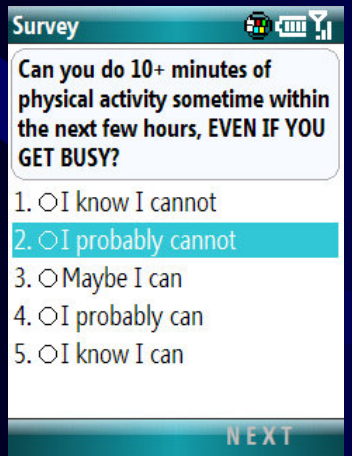


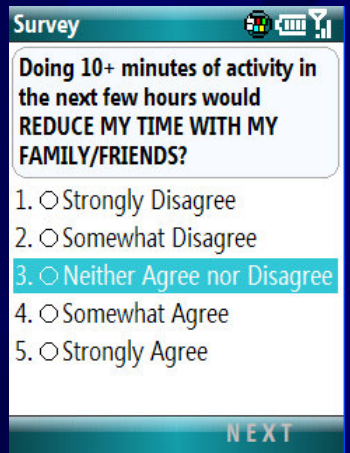






Self-Efficacy (2 items, α = .92)





Accelerometer

- Actigraph GT2M
- Time-stamped and linked with EMA data
- Moderate-to-vigorous physical activity (MVPA) >2200 ct/min (≥ 3 METs)
- Outcome variable: MVPA min in the +60 min after that EMA prompt

PARTICIPANTS

Table 1: Descriptive Characteristics (wave 2)	
N	97
Age	28-74 years (M = 40.6, SD = 9.6)
Sex	72% Female
Ethnicity	34% Hispanic
Income	24% < $40,000/year
Marital Status	66% Married
Weight Status	64% Overweight/Obese

Dynamical Systems Modeling Approach

- Average responses at each time “bucket” over all participants to obtain a time series per construct
- Visualize the data
- Consult experts to determine the proper set of inputs and outputs to examine
- Apply AutoRegressive with eXternal (ARX) estimation
- Validate through multiple measures (goodness of fit, simulation/cross-validation, and step response)

$$\text{goodness-of-fit (\%)} = 100\left(1 - \frac{||y(t) - \tilde{y}(t)||_2}{||y(t) - \bar{y}||_2}\right)$$

Model Structure

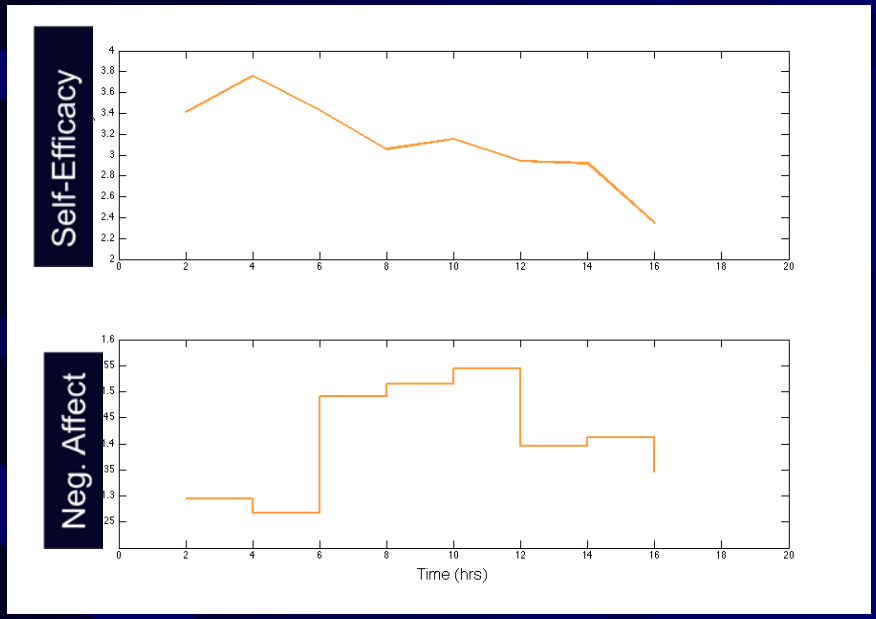
ARX-[n_a n_b n_k] model structure

$$y(t) + ... + a_{n_a} y(t - n_a) = b_{11} u_1(t - n_k) + ... + b_{n_b 1} u_1(t - n_k - n_b + 1)$$
$$\vdots$$
$$+ b_{1i} u_i(t - n_k) + ... + b_{n_b i} u_i(t - n_k - n_b + 1)$$
$$\vdots$$
$$+ b_{1 n_u} u_{n_u}(t - n_k) + ... + b_{n_b n_u} u_{n_u}(t - n_k - n_b + 1) + e(t)$$

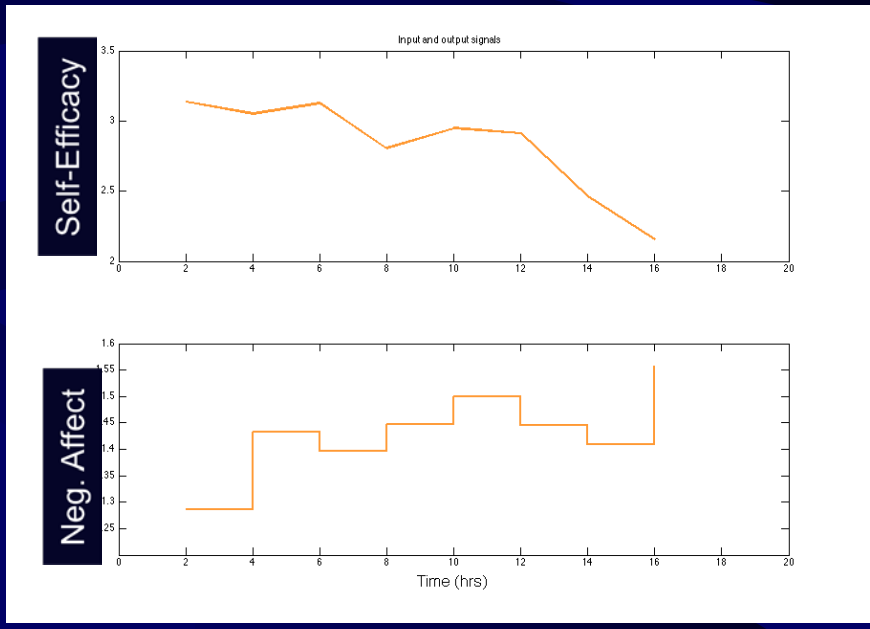
- Lagged set of inputs $u_1(t) \ldots u_{n_u}(t)$ and output $y(t)$
- Parameters readily estimated using linear regression
- Subsequent estimation step can lead to a system of continuous differential equations

Raw Descriptive Data for Input (Neg. Affect) and Output (Self-Efficacy)

Wave 2, Day 1: Saturday



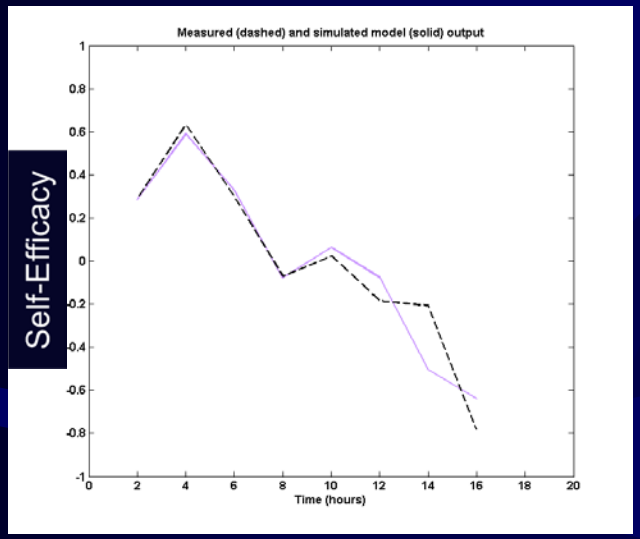
Wave 2, Day 4: Tuesday



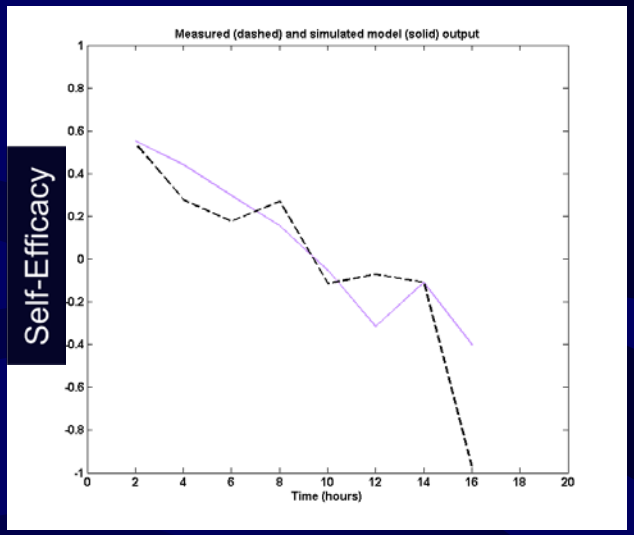
Self-Efficacy as a Function of Neg. Affect

Day 1 (Sat): Fit 68.65%

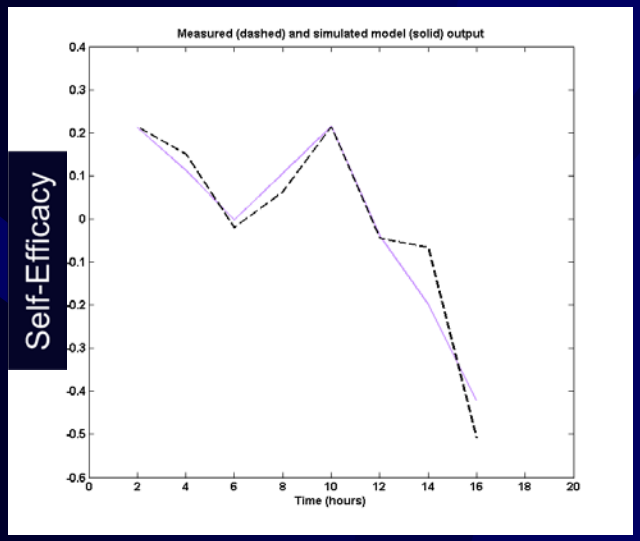
ARX-[4 4 1]



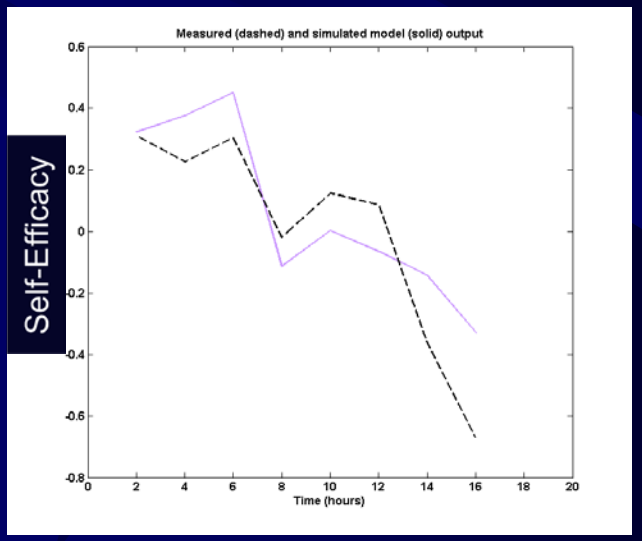
Day 2 (Sun): Fit 44.72%



Day 3 (Mon): Fit 72.68%

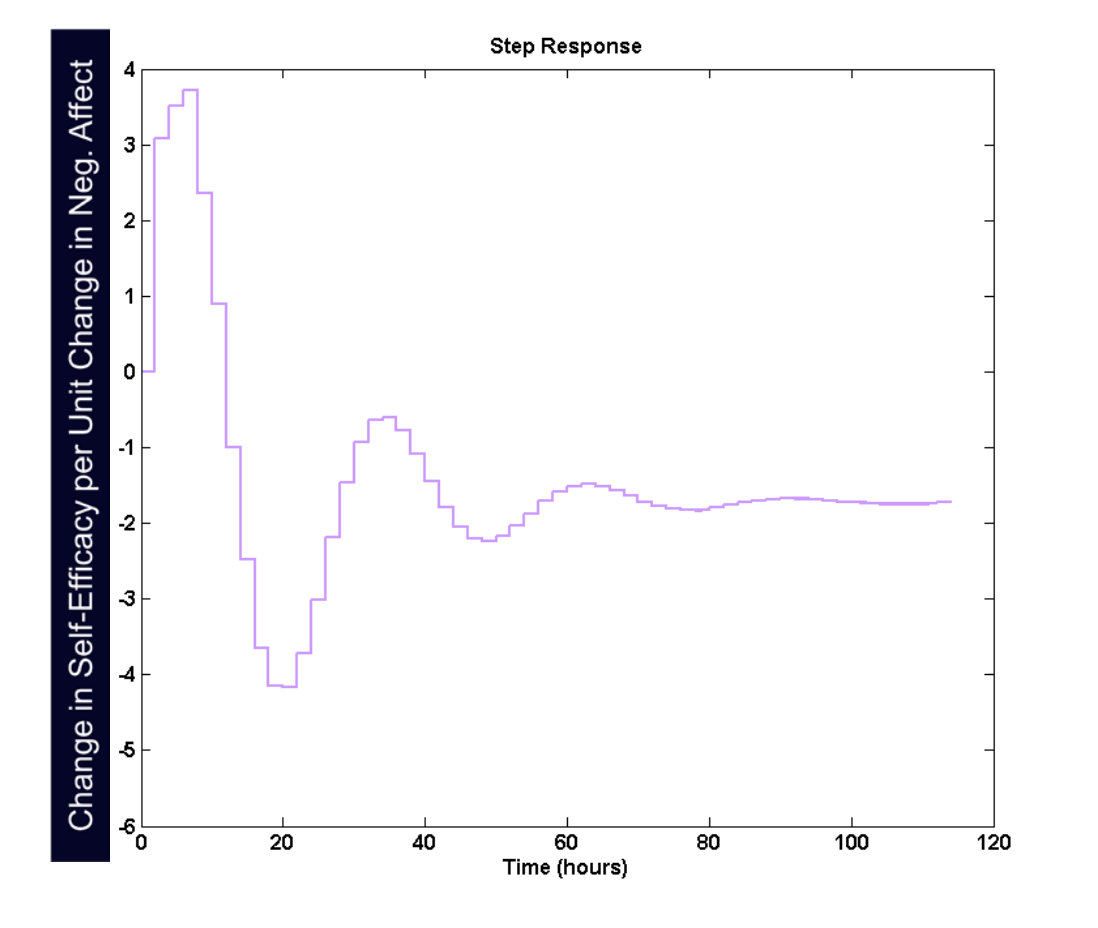


Day 4 (Tues): Fit 45.18%



Step Response for the Relationship Between Neg. Affect and Self-Efficacy

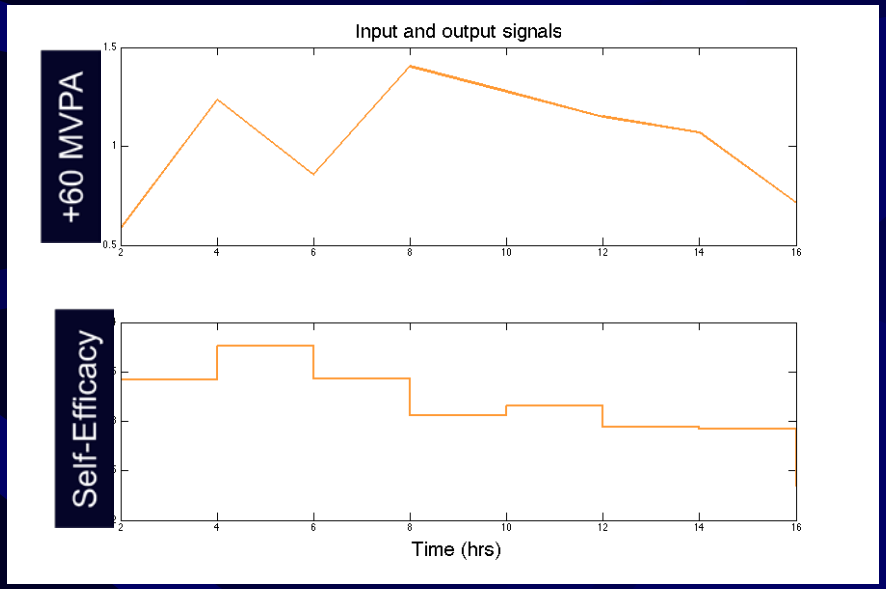
Estimation using days 1-4 ARX-[4 4 1]



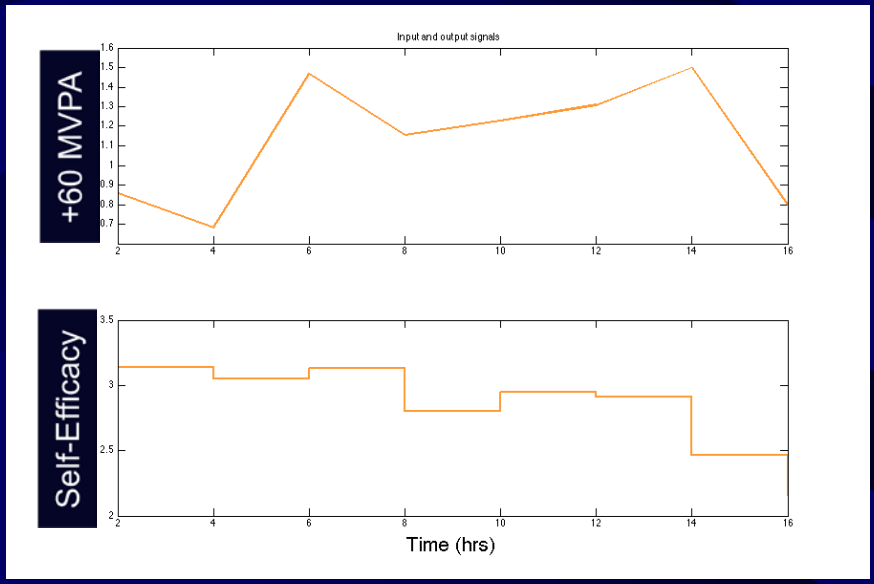
Response is underdamped and shows inverse response.
System gain has sign in the expected direction.

Raw Descriptive Data for Input (Self-Efficacy) and Output (+60 MVPA)

Wave 2, Day 1: Saturday

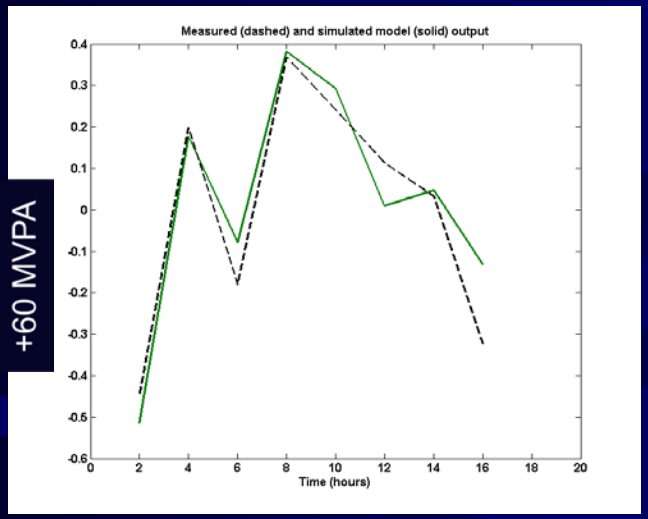


Wave 2, Day 4: Tuesday

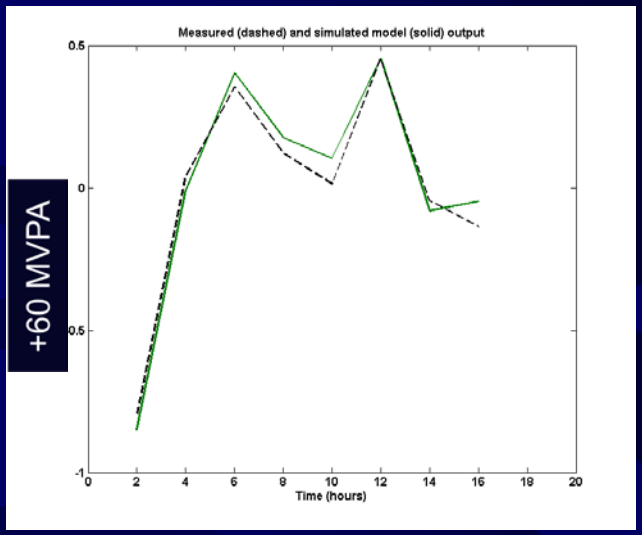


+60 MVPA as a Function of Neg. Affect

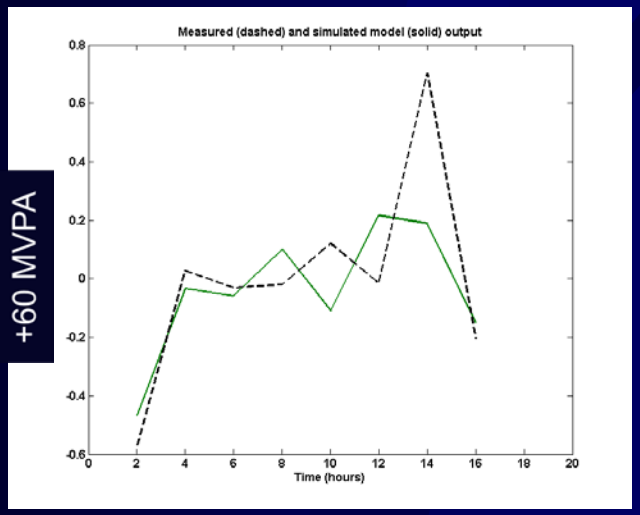
Day 1 (Sat): Fit 66.73% ARX-[4 4 1]



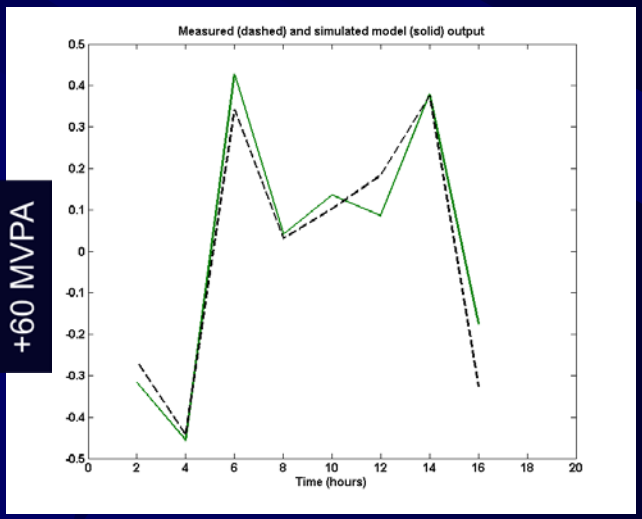
Day 2 (Sun): Fit 83.52%



Day 3 (Mon): Fit 32.52%

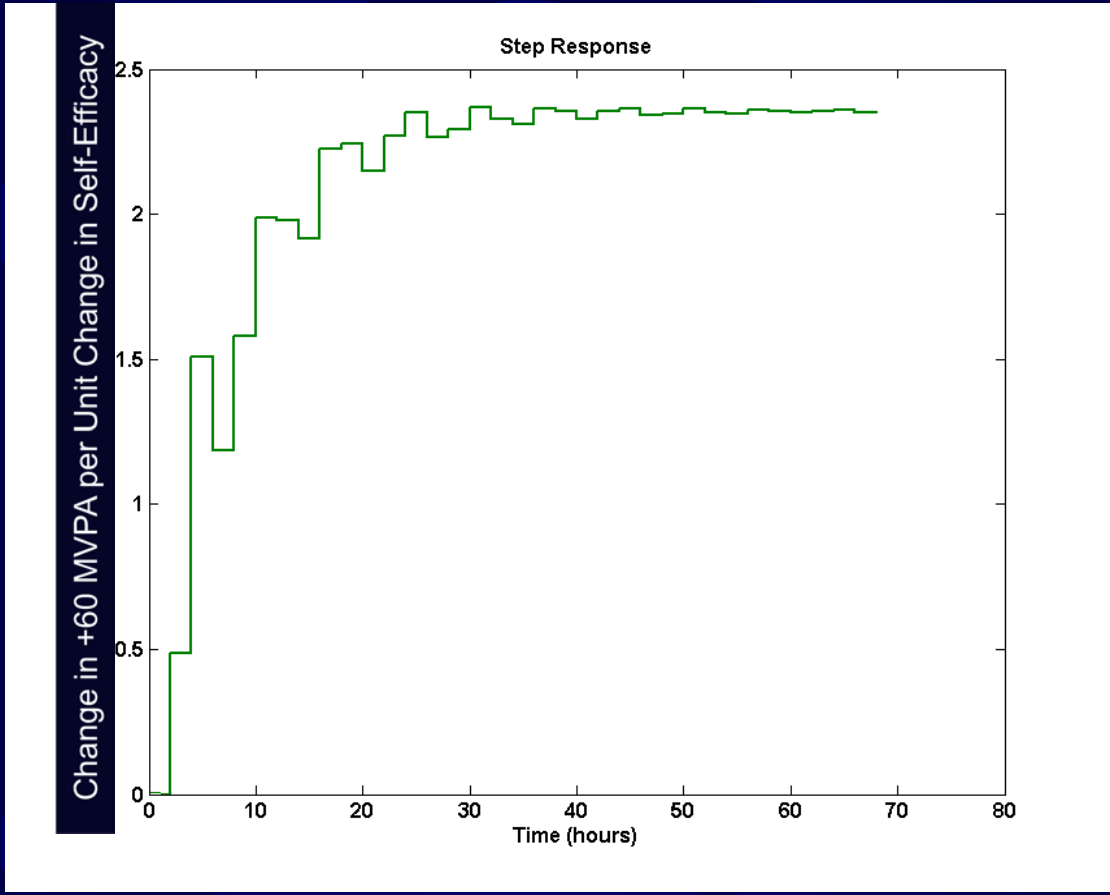


Day 4 (Tues): Fit 74.63%



Step Response for the Relationship Between Neg. Affect and Self-Efficacy

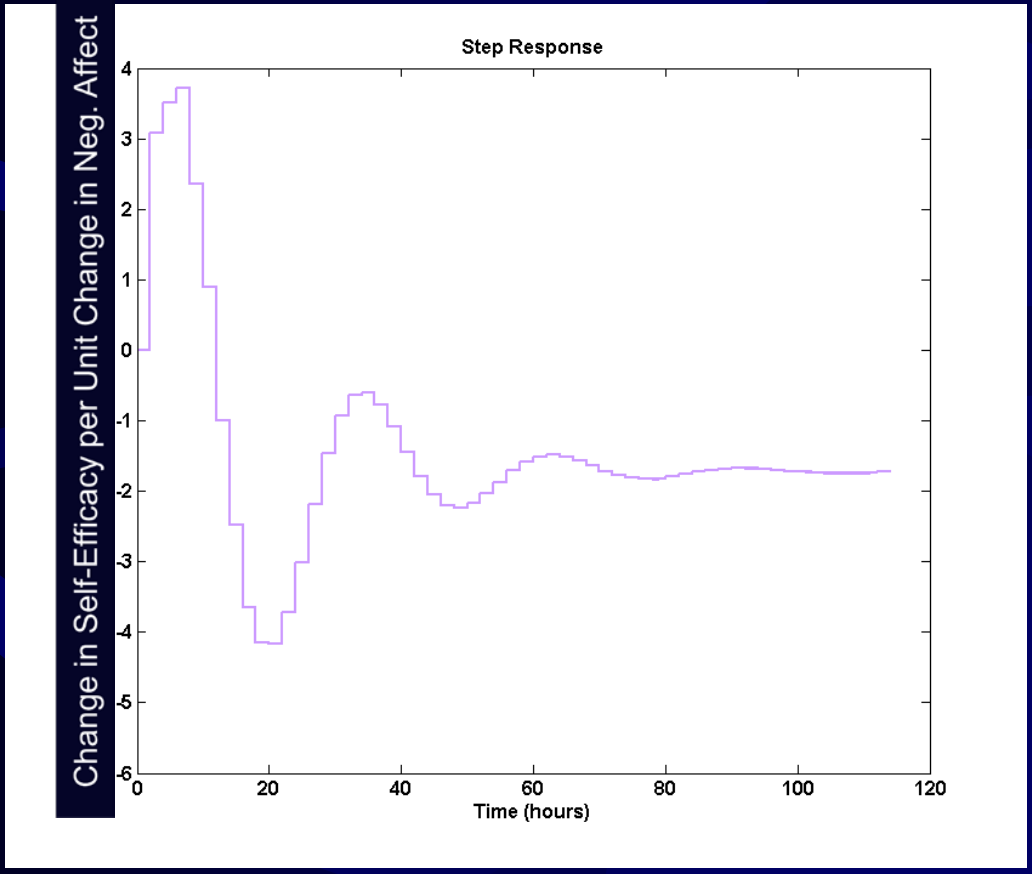
Estimation using Days 1-4 ARX-[4 4 1]



Some Observations

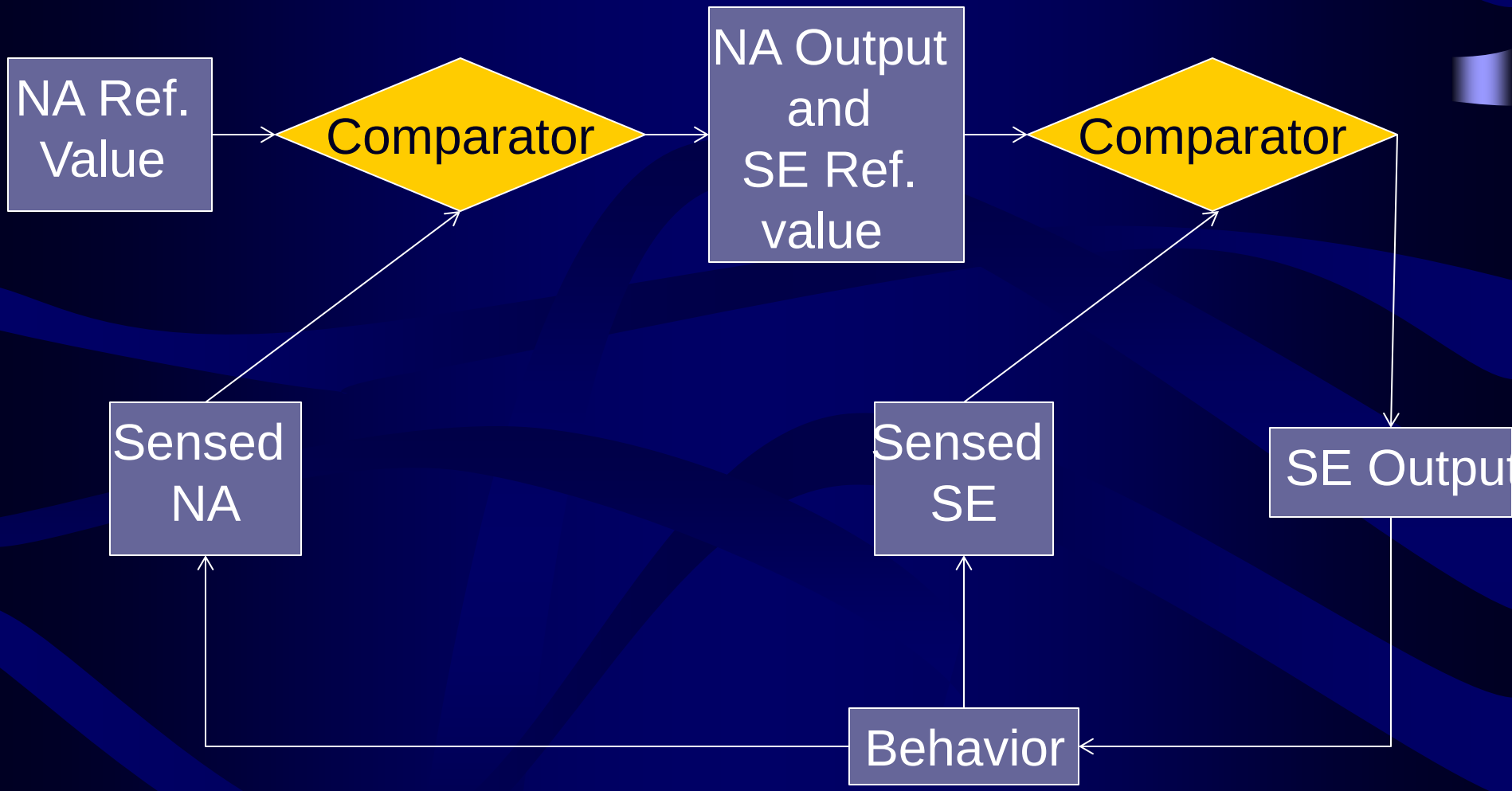
- Many possibilities exist for examining the data exhaustively, based on per day, weekend vs. weekday, discrete-time vs. continuous-time models, etc.
- Each day has its own interesting dynamics; eight data points, however, limited what could be estimated at a single day level.
- Including additional days facilitated the use of higher-order models and gave greater flexibility to the estimator, at the expense of better knowledge of differences between days, weekend vs. weekday, etc.
- Many possibilities for cross-validation that need to be further investigated.
- As a observational study, limited excitation impacts the results (particularly in the self-efficacy modeling).

Negative Affect → Self-efficacy: Underdamped Response



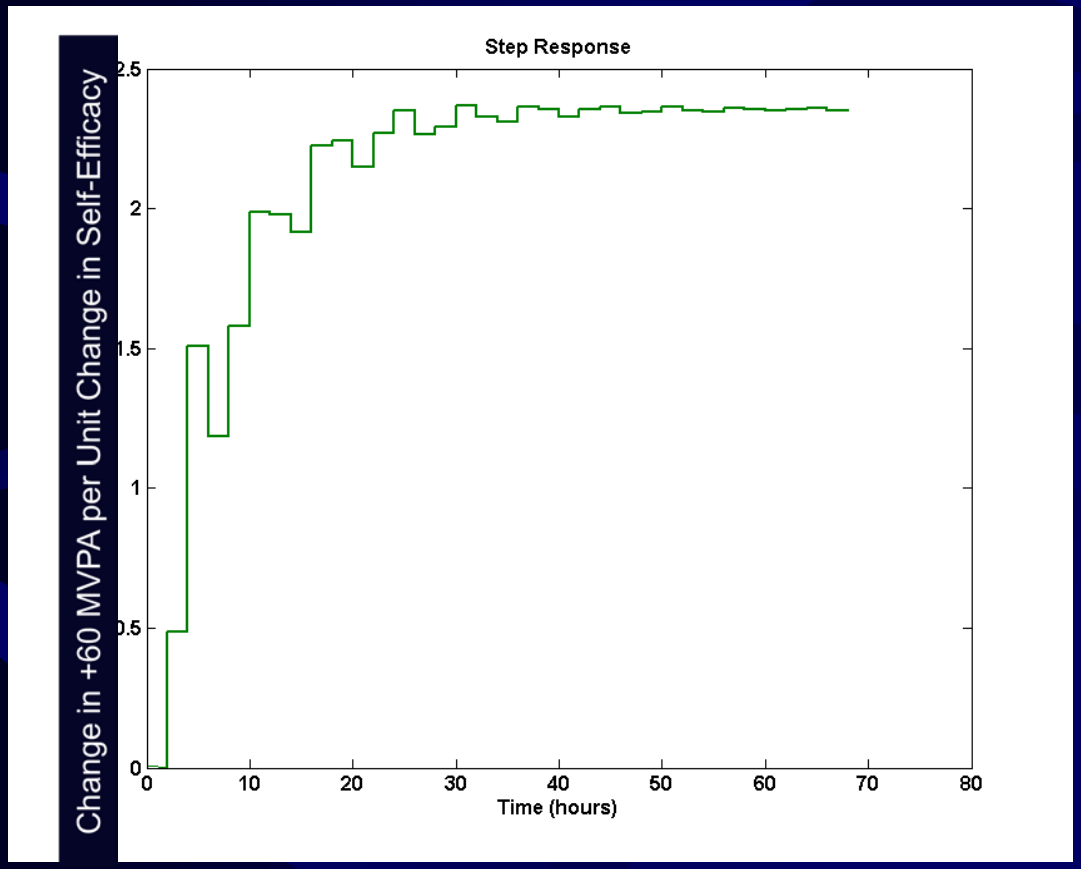
- Oscillating pattern with initial "inverse response"
- Highly transient/short-term effects
- Within-person changes in direction of association
- Denotes "aggressive" or "over-compensatory" control "at the threshold of stability"

Systems Theory of Self-Regulation



Carver & Scheier, 1990, 1998

Self-Efficacy → MVPA: Overdamped Response



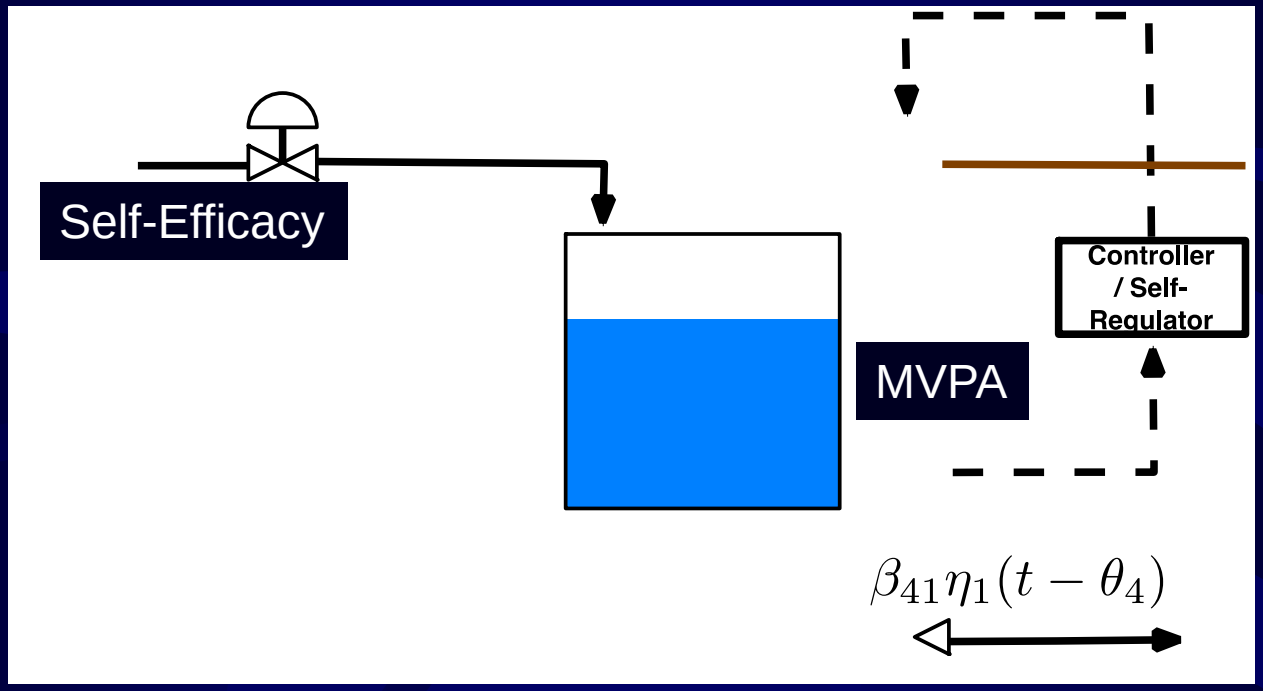
Possibility #1

- Closed-loop system with a well-tuned controller
- Negative Feedback

Possibility #2

- Open-loop system reflecting a basic accumulation-depletion process (i.e., fluid analogy)

Fluid Analogy Depicting Self-Regulation



The fluid analogy depicts accumulation-depletion of the output (*MVPA*) as a result of changes in the input (*self-efficacy*). A controller / self-regulator relying on a sensed value of the output attempts to compensate for the input change, resulting in potentially significant variability.

Comparable Systems Theories in Psychology/Biology

Underdamped response (over-compensatory self-regulation)

- Stress-induced shift from goal-directed to habit behavior (Schwabe & Wolf, 2009, 2010)
- General Adaptation Syndrome (Selye)

Overdamped response (well-tuned self-regulation)

- Goal-directed behavior (Carver & Scheier)
- Ideal/ought selves, approach/avoidance (Higgins)

Ongoing Issues/Challenges to Consider

- Consider revisiting the experimental
  - Generate a more time-intensive data set
  - Facilitate cross-validation
  - Measure and/or revise constructs to enable more persistent excitation in the data, reduce correlations between signals and allow for "reverse-engineering" the self-regulator
- Examine model structures that include nonlinearity or time-varying parameters
- Apply methods for estimating differential equations that are more in line with statistical methodological approaches (e.g., Trail et al., *Psych Methods*, in press).

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