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Methods: Mind the Gap

Webinar Series

Optimizing Behavioral mHealth Interventions Using Control Systems Engineering: The Control Optimization Trial

Presented by:

Daniel E. Rivera, Ph.D.
Arizona State University

National Institutes of Health
Office of Disease Prevention

Optimizing Behavioral mHealth Interventions using Control Systems Engineering: The Control Optimization Trial

Daniel E. Rivera, Ph.D.

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Talk Objectives

- To show how control systems engineering, coupled with system identification and behavior change theories, can lead to decision algorithms for achieving *personalized, adaptive, and optimized behavioral interventions*.
- Introduce the Control Optimization Trial (COT) as an effective means for achieving these interventions.

Some Caveats

- CAVEAT No. 1: As an engineer, *engineering sensibilities* will feature prominently in the talk.
- CAVEAT No. 2: Approach presented will be *idiographic* (i.e., single-subject) in nature.
- CAVEAT No. 3: The Control Optimization Trial is a concept that remains under development.

Key References

JOURNAL OF MEDICAL INTERNET RESEARCH Hekler et al

Tutorial

Tutorial for Using Control Systems Engineering to Optimize Adaptive Mobile Health Interventions

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Abstract

Background: Adaptive behavioral interventions are individualized interventions that vary support based on a person's evolving needs. Digital technologies enable these adaptive interventions to function at scale. Adaptive interventions show great promise for producing better results compared with static interventions related to health outcomes. Our central thesis is that adaptive interventions are more likely to succeed at helping individuals meet and maintain behavioral targets if its elements can be iteratively improved via data-driven testing (ie, optimization). Control systems engineering is a discipline focused on decision making in systems that change over time and has a wealth of methods that could be useful for optimizing adaptive interventions.

Objective: The purpose of this paper was to provide an introductory tutorial on when and what to do when using control systems engineering for designing and optimizing adaptive mobile health (mHealth) behavioral interventions.

Overview: We start with a review of the need for optimization, building on the multiphase optimization strategy (MOST). We then provide an overview of control systems engineering, followed by attributes of problems that are well matched to control engineering. Key steps in the development and optimization of an adaptive intervention from a control engineering perspective are then summarized, with a focus on why, what, and when to do subtasks in each step.

Implications: Control engineering offers exciting opportunities for optimizing individualization and adaptation elements of adaptive interventions. Arguably, the time is now for control systems engineers and behavioral and health scientists to partner to advance interventions that can be individualized, adaptive, and scalable. This tutorial should aid in creating the bridge between these communities.

(J Med Internet Res 2018;20(6):e214) doi:10.2196/jmir.8622

KEYWORDS
adaptive interventions; mHealth; eHealth; digital health; control systems engineering; behavior change; optimization; multiphase optimization strategy; physical activity; behavioral maintenance

http://www.jmir.org/2018/6/e214/ J Med Internet Res 2018 | vol. 20 | iss. 6 | e214 | p.1 *(page number not for citation purposes)*

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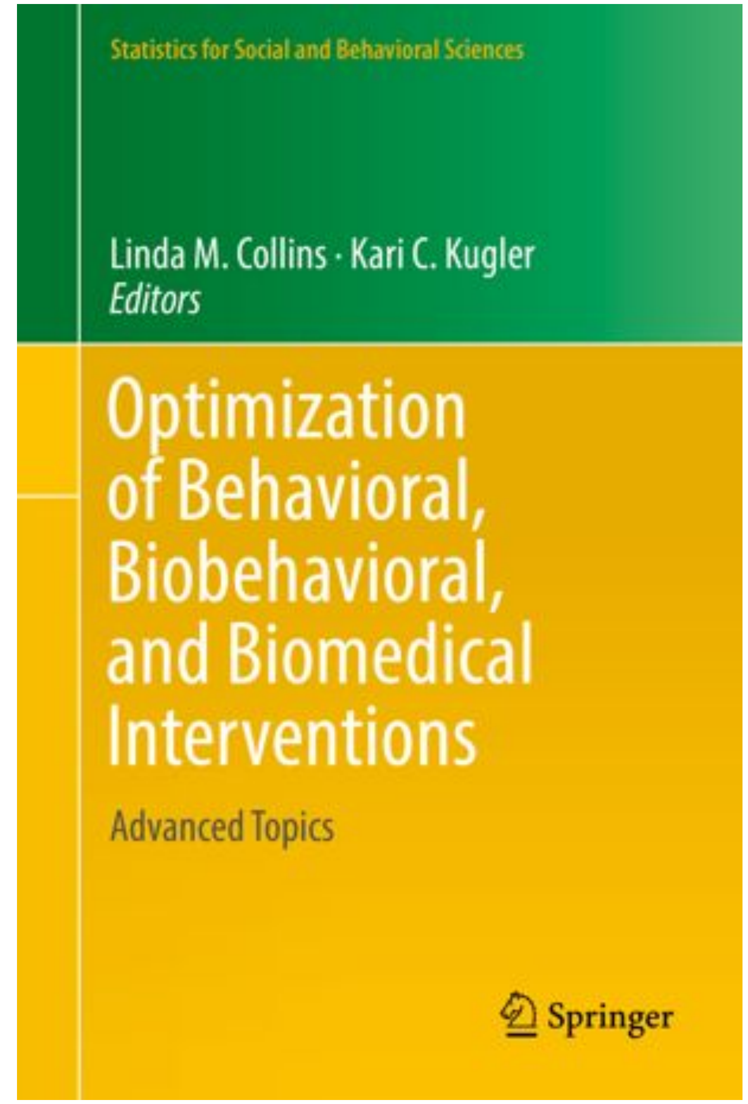

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Helpful References

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Just Walk "Modeling and More" Team (NSF IIS-1449751, R01CA244777)

- Left: Eric Hekler (Director, Center for Wireless and Population Health, Qualcomm Center, and UCSD Design Lab; Dept. of Family and Public Health); Right: *Just Walk* team at ASU campus, 2016.

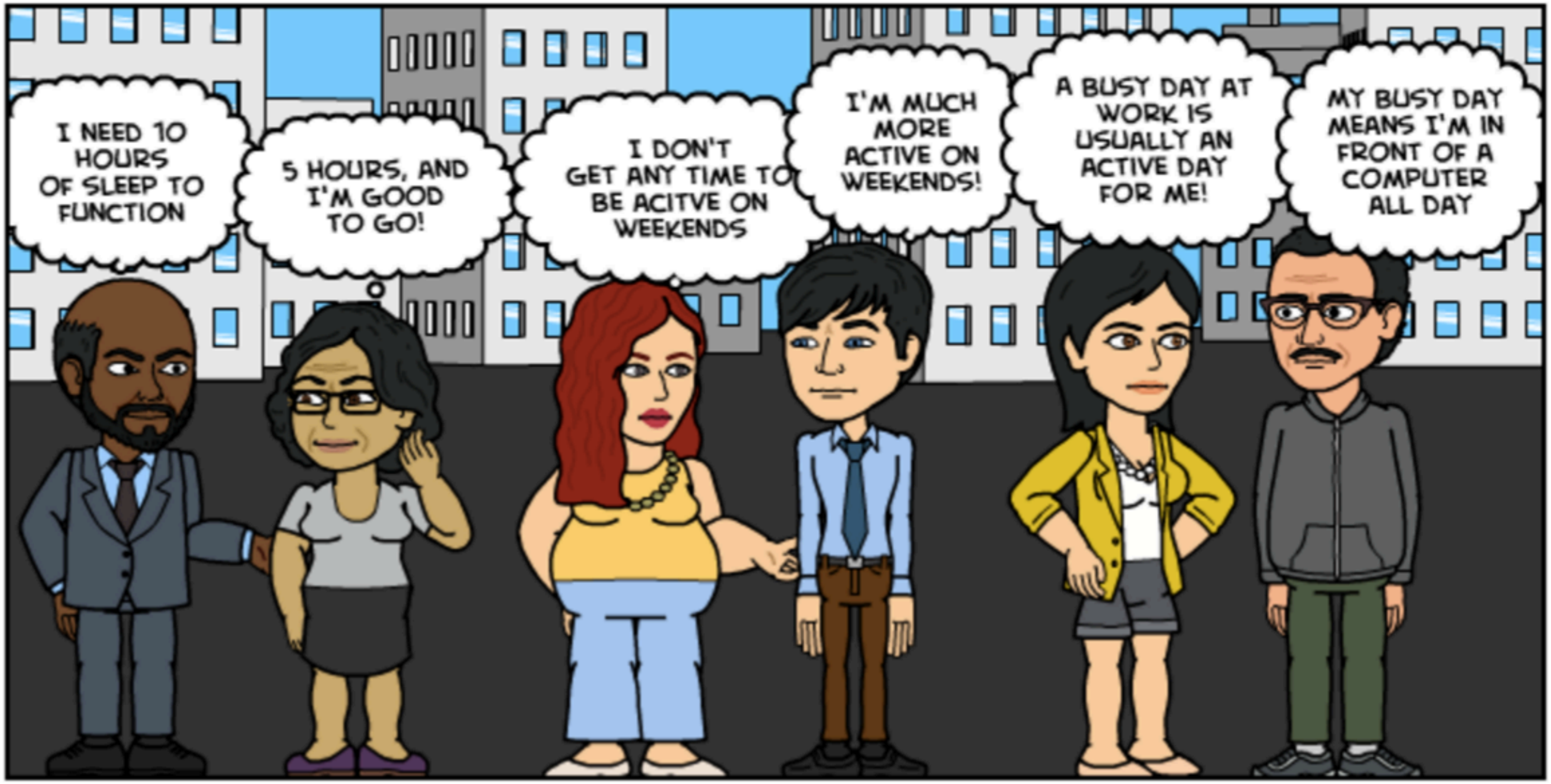
Health Mom Zone Study (R01 HL119245)

Dr. Danielle Symons Downs
Pennsylvania State University

Dr. Jennifer Savage Williams
Pennsylvania State University

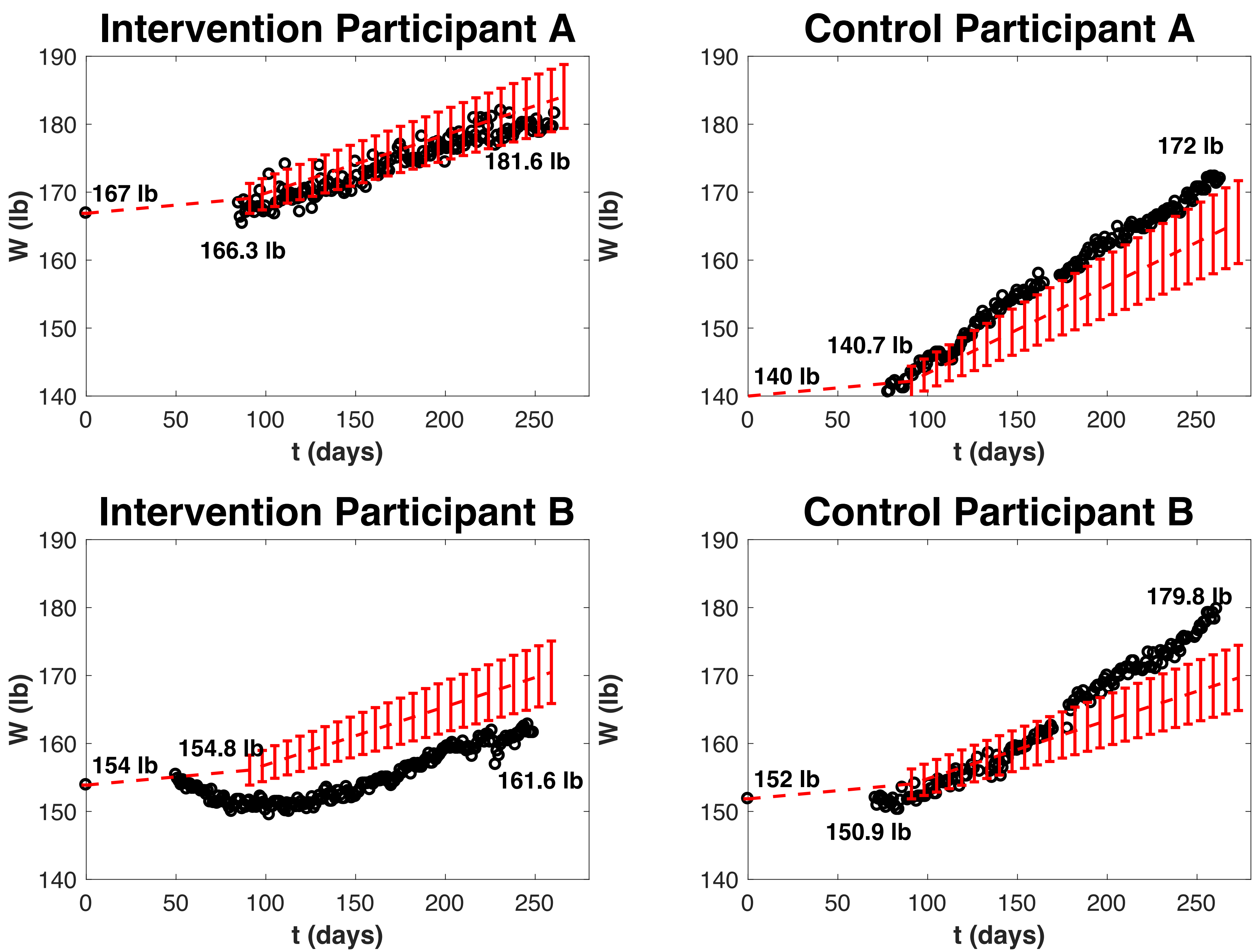
- Danielle Symons Downs (Kinesiology, PI) and Jennifer Savage Williams (Nutritional Sciences, co-I).

Need for Personalized and *Perpetually Adapting* Interventions



- Understanding individual differences (across participants and over time) is critically important.

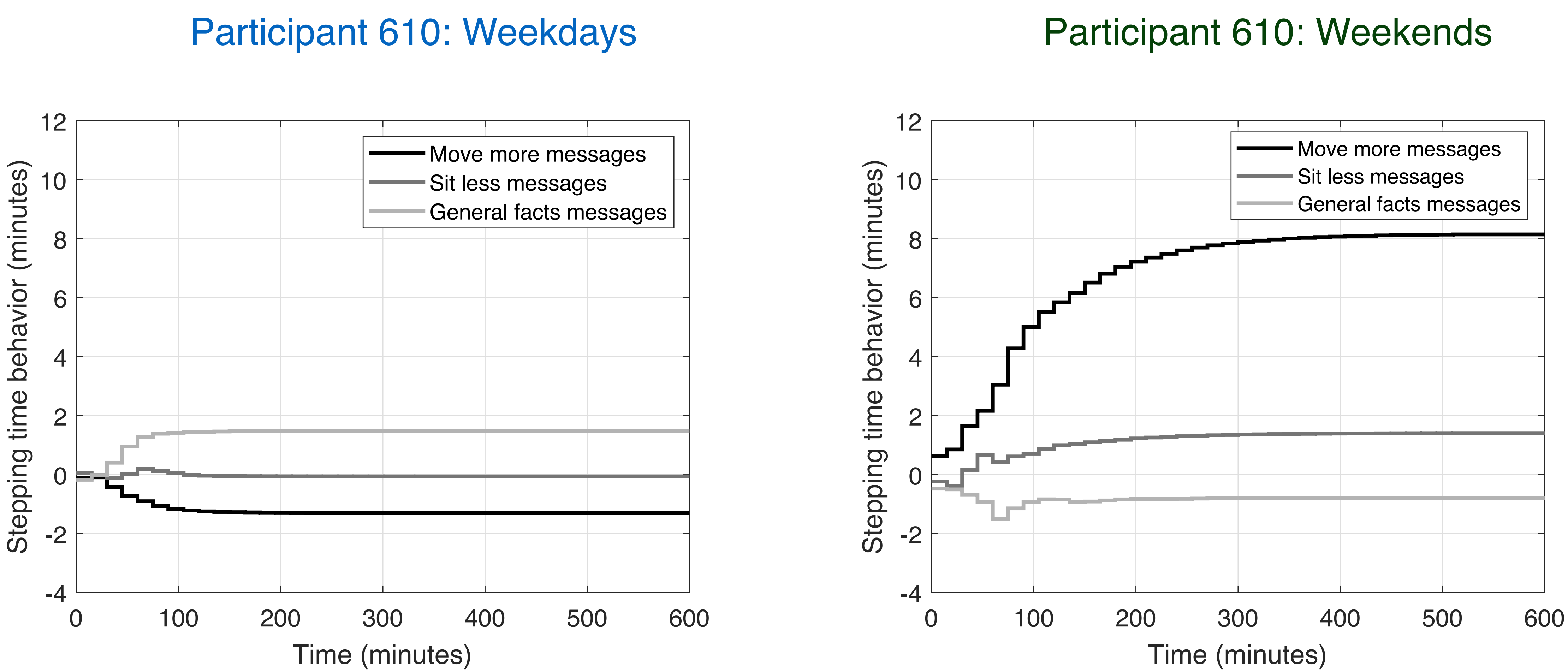
Healthy Mom Zone Study (R01 HL119245, Symons Downs, PI)
Representative Participants - Phase 2



- Red curve/bars represent Institute of Medicine (IOM) guidelines

Physical Activity Response to Text Messages

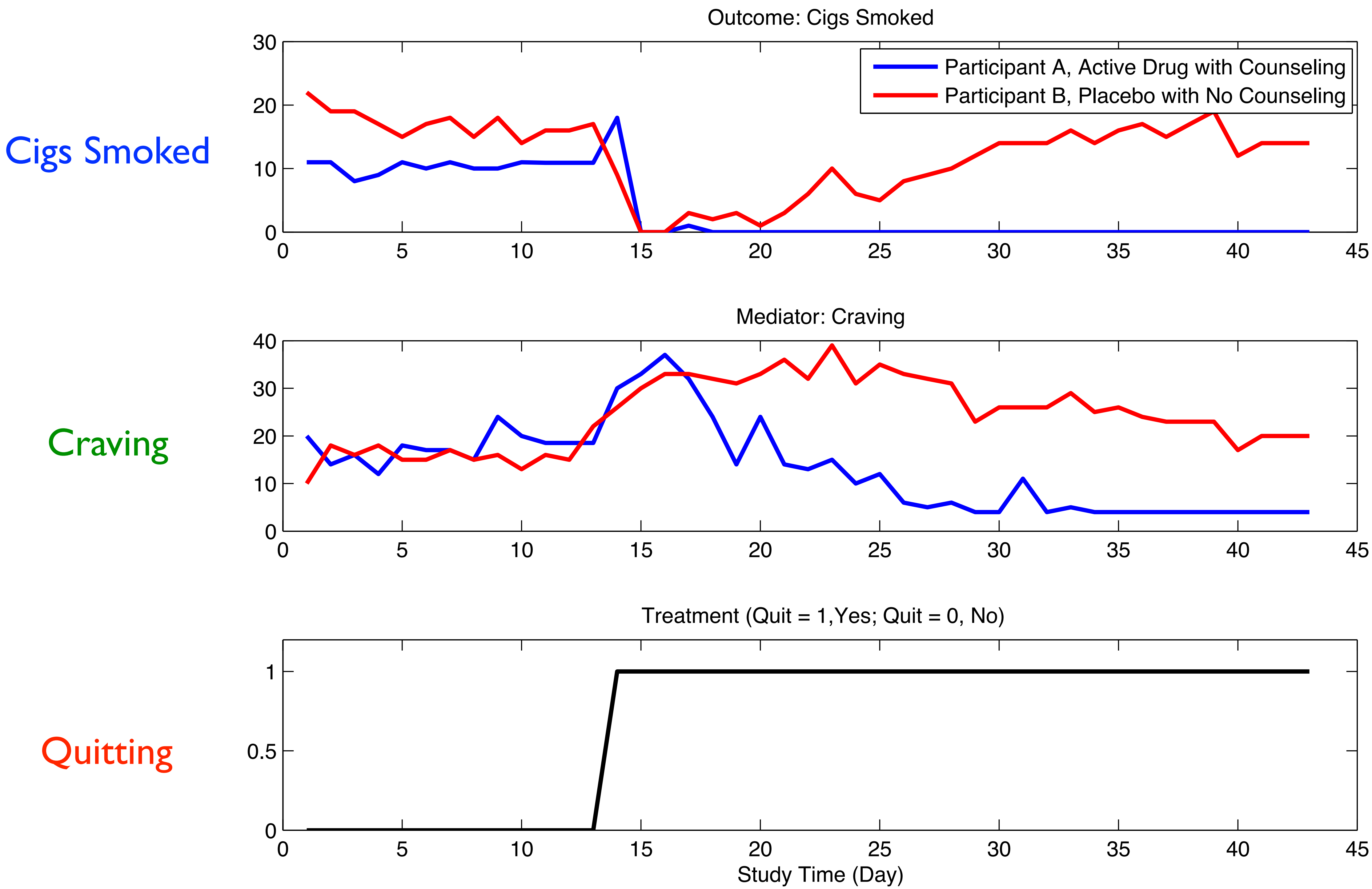
From: Conroy DE, Hojjatinia S, Lagoa CM, Yang C-H, Lanza ST, Smyth JM., *Psychol. Sport Exerc.* 2019; 41:172–80.



- Physical activity responses for one (of 10) participants to a text message intervention as a proof-of-concept application of control systems engineering.
- Results show clear dynamic behavior and heterogeneity of response.

UW-CTRI Smoking Cessation Study

McCarthy *et al.*, *Addiction*, Vol. 103, pgs. 1521-1533, 2008



- Participant "A" from drug group (blue); participant "B" from placebo group (red)

Common Features

- Lagged dynamic behavior showing distinctive characteristics (e.g., integrating, overdamped, inverse response)

- Outcome variables and other important variables can be measured intensively.

- Multiple intervention options and frequent decision points are available.

- Previous theory and evidence are available to guide intervention development (i.e., the question to answer is not “IF” but “HOW”).

Control Systems Engineering

- The field that relies on *dynamical systems models* to develop algorithms for adjusting system variables so that their behavior over time is transformed from *undesirable* to *desirable*.

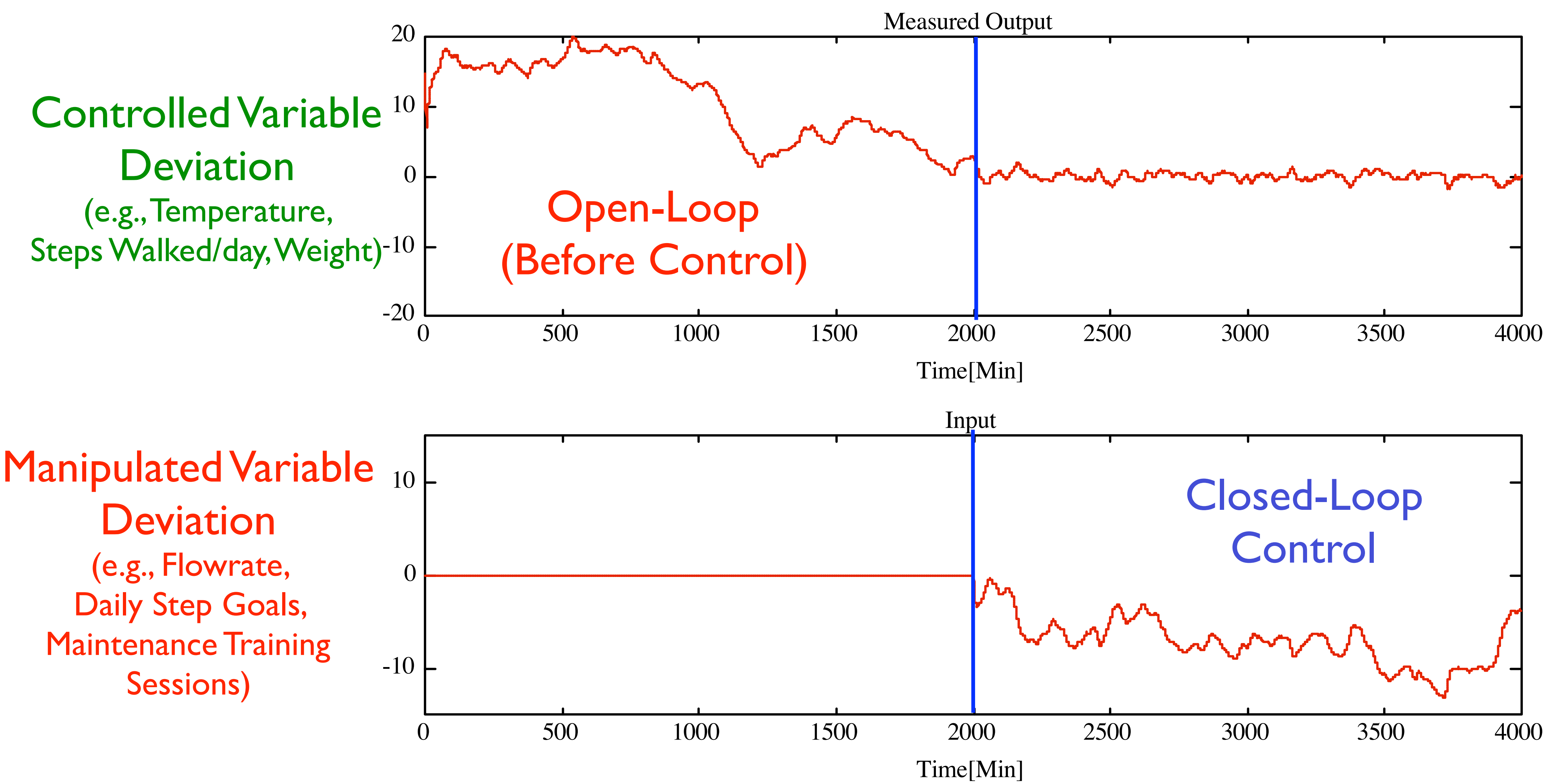
- Control engineering plays an important part in many everyday life activities. Some examples of control systems engineering :

    - Cruise control and climate control in automobiles,
    - Home heating and cooling,
    - The artificial pancreas for Type-I diabetics,
    - Fly-by-wire systems in high-performance aircraft.

- Many other examples (including success stories and grand challenges) are presented in http://ieeecss.org/general/impact-control-technology.

From “Open-Loop” Operation to “Closed-Loop” Control

- A well-tuned control system will effectively *transfer variability* from an important system variable to a less important one.



The transfer of variance (as depicted in this diagram) represents one of the major benefits of control systems engineering.

Navigation Autopilot

- Courtesy of Eric Hekler

Control Engineering Approach

- Development of dynamical models from data via *system identification* (a method that can be informed by behavior change theories).

- Design of decision algorithms/decision “rules” through model-based methodologies such as Model Predictive Control (MPC).

The *Just Walk* Intervention Study
Sponsor: NSF Smart and Connected Health (SCH) Program

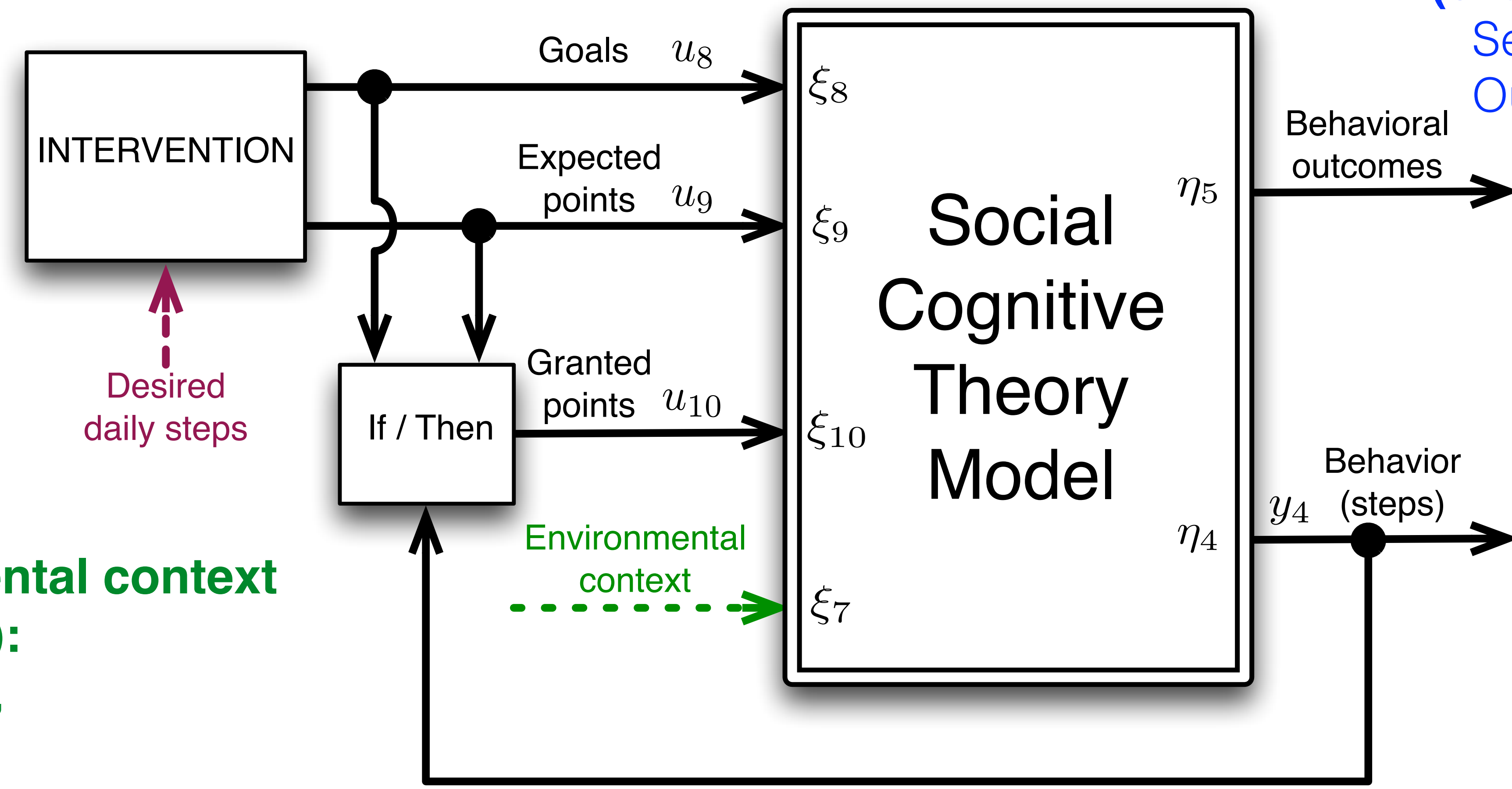
- *Just Walk* is an idiographic mHealth intervention to promote physical activity in sedentary adults based on *control systems engineering*.
- *Just Walk v1* relies on an experimental procedure using *system identification* to build a *dynamical systems model* that helps explain how step goals, rewards, and external factors influence walking.
- *Just Walk v1* is <u>not</u> a fully optimized intervention, but represents the first phase of a <u>*control optimization trial (COT)*</u>, which is part of *Just Walk v2*.
- *N = 20* participants, 90% female, mean age = 47.25 ± 6.16 years, mean BMI = 33.79 ± 6.82 kg/m^2.

Just Walk Intervention

The intervention seeks to promote physical activity (e.g., walking/running) among inactive adults by adjusting *daily step goals* and *expected reward points*, with the ultimate goal of reaching 10,000 steps per day (on average) per week.

Behavioral Outcomes (examples):

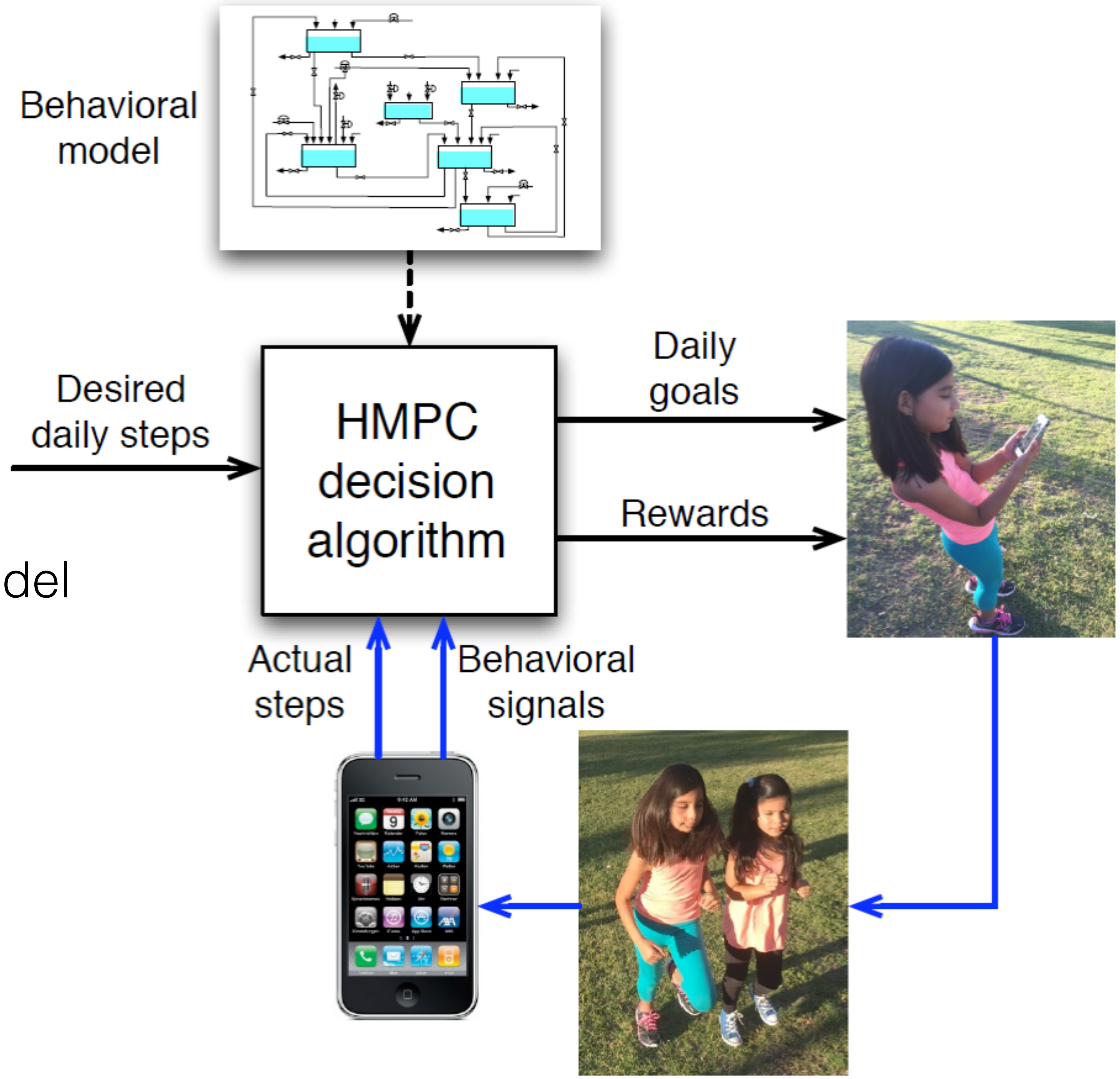
Self-Efficacy
Outcome Expectancies



Environmental context (examples):

Busyness,
Stress,
Weather,
Weekday or weekend

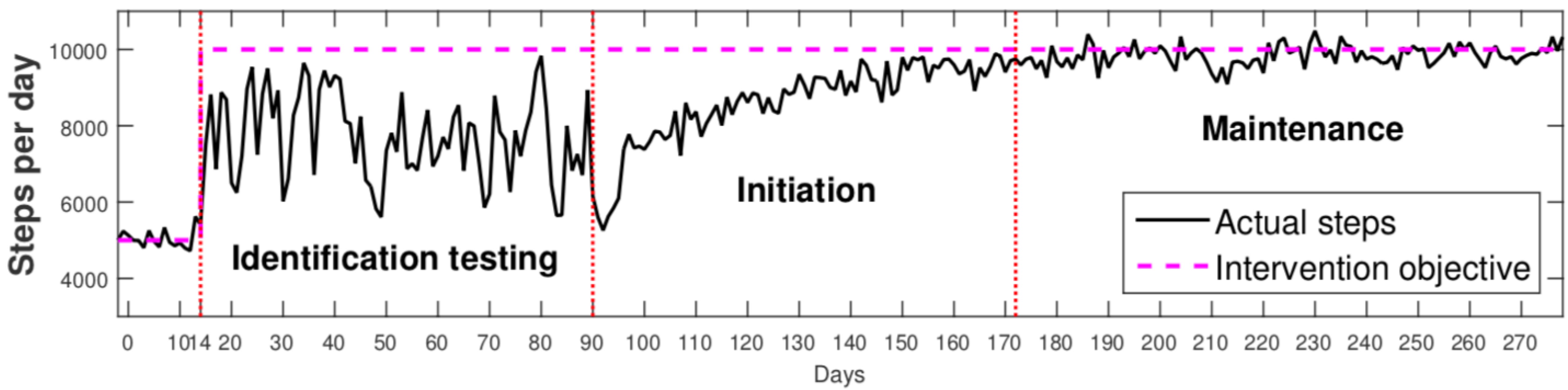
Closing the Intervention Loop: *Just Walk*



HMPC = Hybrid Model Predictive Control

C. A. Martín, D. E. Rivera and E. B. Hekler, "A decision framework for an adaptive behavioral intervention for physical activity using hybrid model predictive control," *2016 American Control Conference (ACC)*, Boston, MA, 2016, pp. 3576-3581.

The Control Optimization Trial (COT)

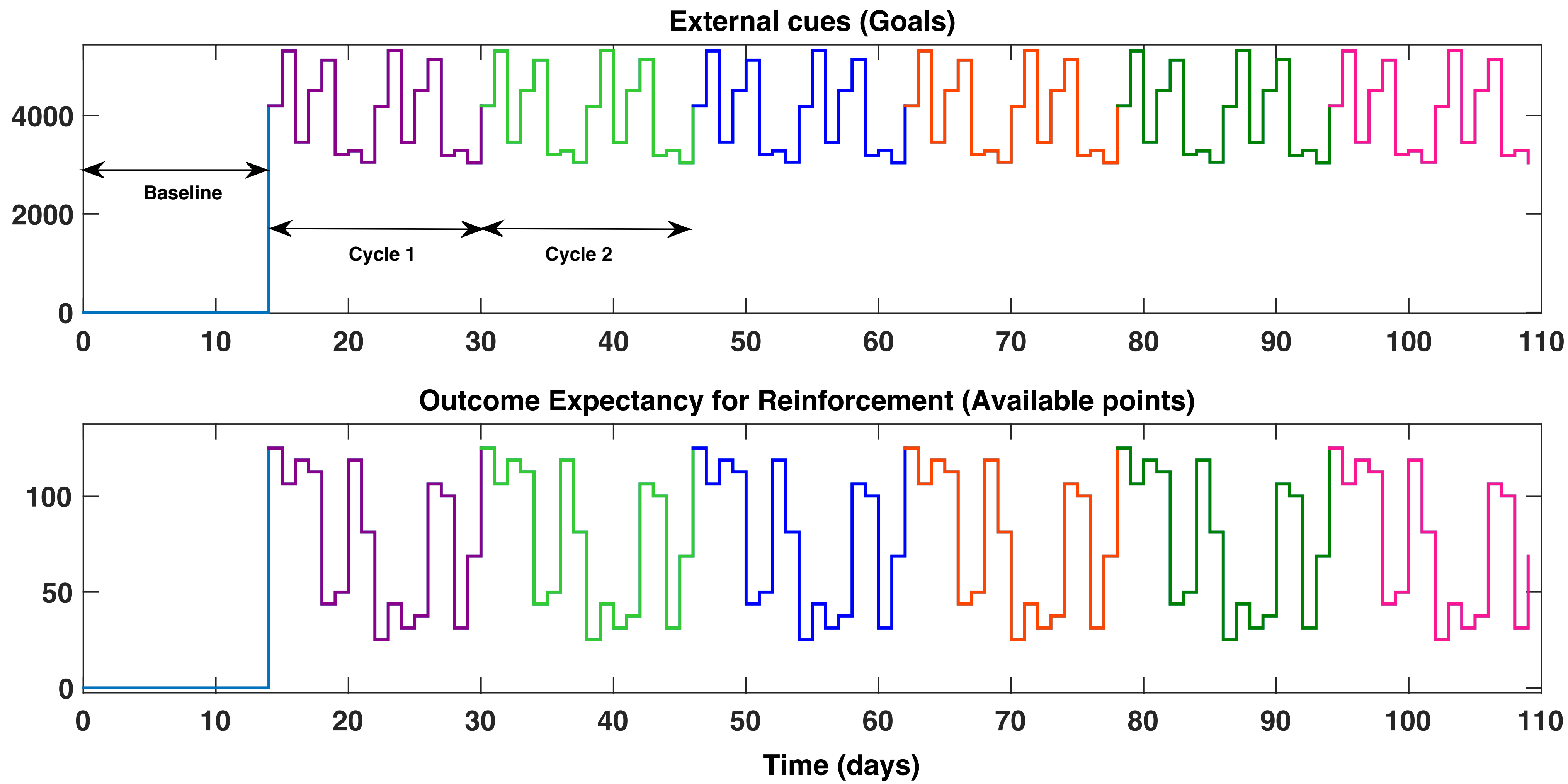


- A *informative* identification test provides the data needed to estimate a dynamical system model that can predict participant response to changes(in dosage and context).

- *Initiation* and *maintenance* accomplished by a decision algorithm ("controller") that relies on a dynamical model to decide the magnitude and timing of intervention components.

“Zippered” Multisine Inputs used in *Just Walk v1*

Box, Hunter, and Hunter (Statistics for Experimenters), *“to find out what happens when you change something it is necessary to change it.”*



- Goal range: doable (baseline median) to ambitious (2.5x baseline median).
- These are “pseudo-random”, statistically independent signals.
- 16-day cycles implemented, five or six per participant, over approximately 12 weeks.

Estimating Dynamical System Models

- Black-box, “ready-made” prediction-error models (e.g., ARX),
- Mechanistic, semi-physical models based on behavioral theories,
  - Theory of Planned Behavior
  - Social Cognitive Theory

ARX Model Estimation Procedure

- *Data Preprocessing*: The data is preprocessed for missing entries.

- *Discrete-time parametric modeling*: The filtered data is fitted to a multi-input AutoRegressive with eXternal input (ARX-[*na nb nk*]) parametric model:

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

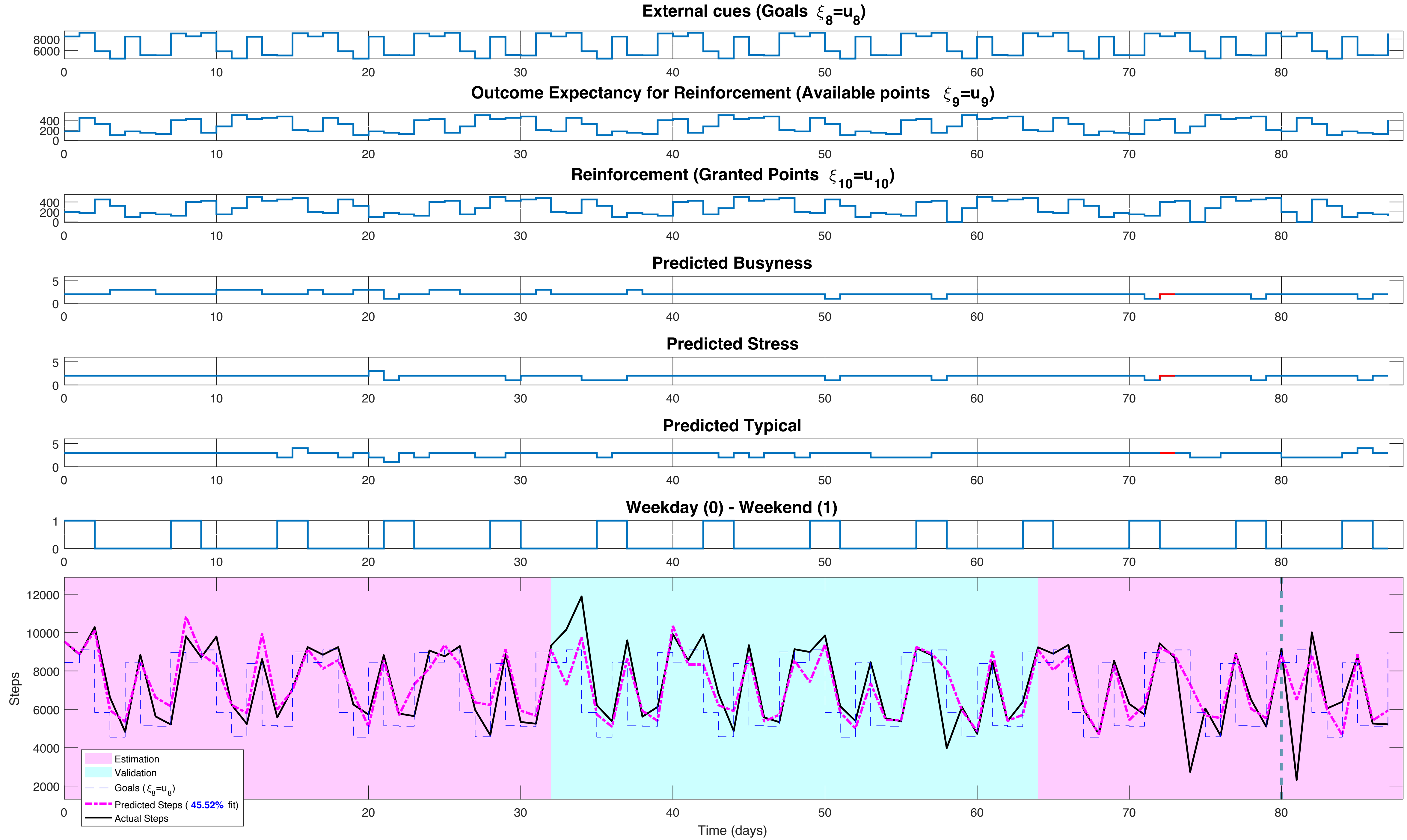
- *Validation*: Various measures used, among these the Normalized Root Mean Square Error (NRMSE) fit index:

$$\text{model fit } (\%) = 100 \times \left(1 - \frac{||y(k) - \hat{y}(k)||_2}{||y(k) - \bar{y}||_2}\right) \tag{1}$$

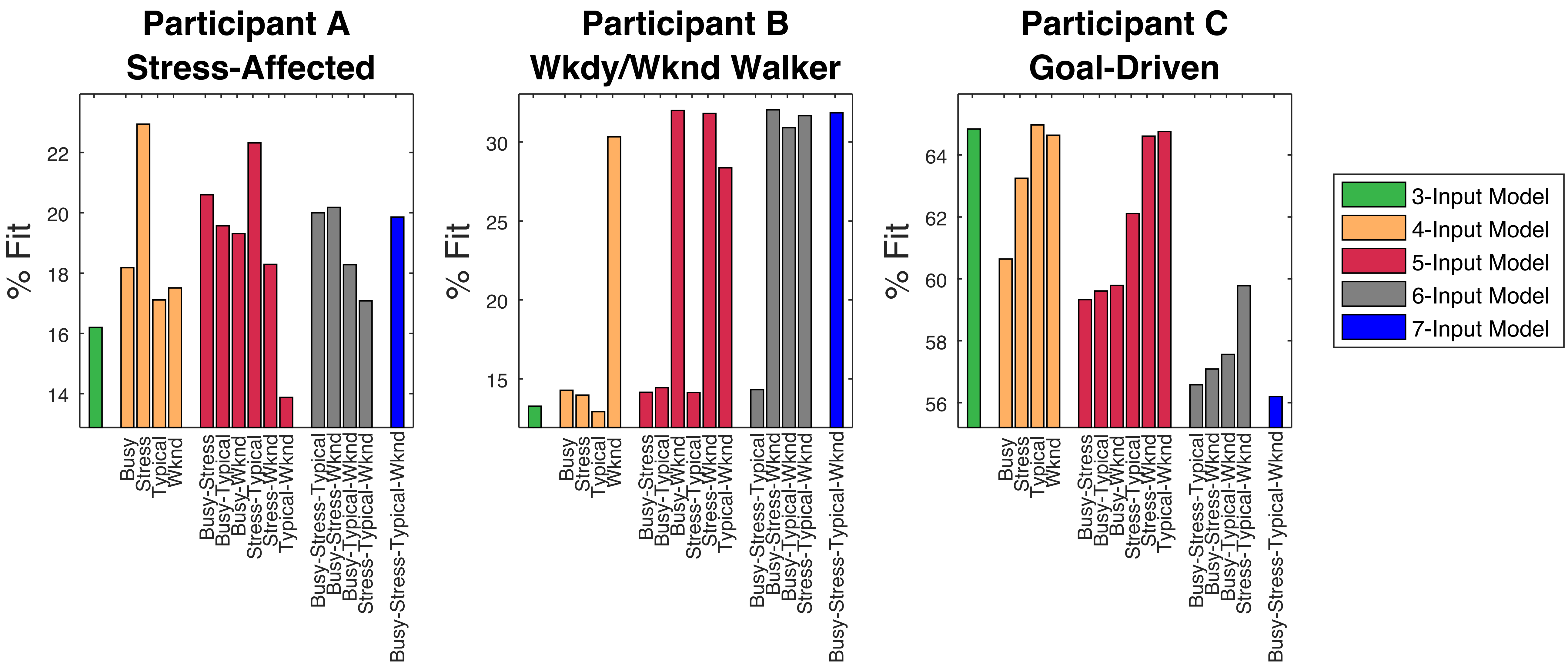
$y(k)$ is the measured output, $\hat{y}(k)$ is the simulated output, $\bar{y}$ is the mean of all measured $y(k)$ values, and $||\cdot||_2$ indicates a vector 2-norm ($\|x\|_2 \stackrel{\text{def}}{=} \sqrt{x^T x}$).

Subset of *Just Walk* Signals (Participant 100230)

Time series plot showing seven selected input sequences (manipulated inputs & measured disturbances), predicted behavior (from an ARX black-box model), actual behavior, model overall fit, and estimation & validation cycles (1st, 2nd, and 5th for estimation; 3rd and 4th for validation).



Global Validation Overview: Idiosyncrasy



- Individualized ARX models from black-box system identification for three individuals: *Goals*, *Expected Points*, and *Granted Points* models; **B**: *Predicted Busyness*; **S**: *Predicted Stress*; **T**: *Predicted Typical*; **W**: *Weekday-Weekend*.
- *Participant A* shows no model fit improvement beyond a 4-input model including predicted stress (S).
- *Participant B* displays significant model fits only with the inclusion of the weekday-weekend input signal.
- *Participant C* shows no model fit improvement beyond the 3-input model (with goals driving the behavior-change).

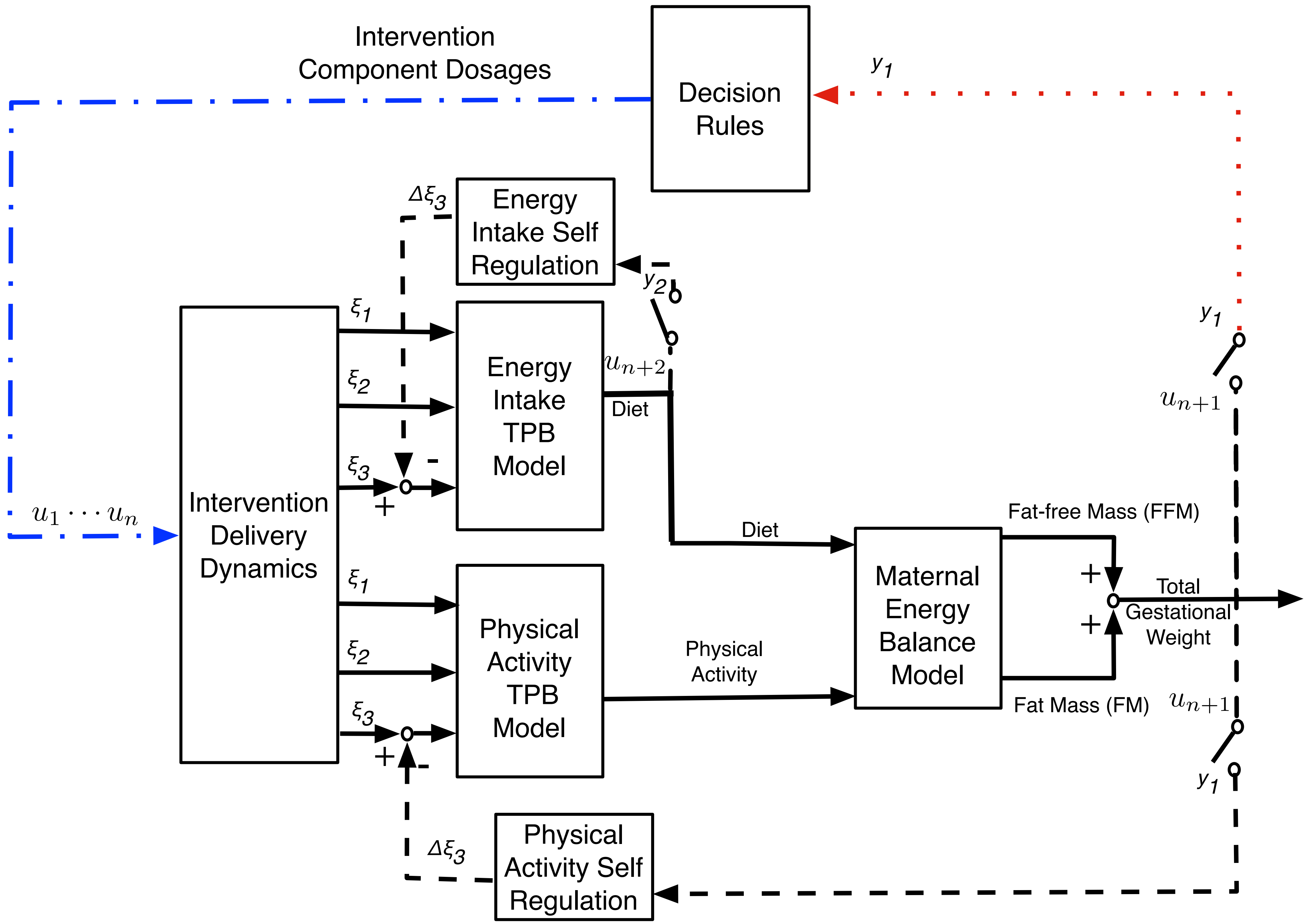
Gestational Weight Gain Adaptive Intervention Overview

Healthy Mom ZONE

PENNSTATE Exercise Psychology Laboratory

- Lead behavioral scientists are Danielle Downs (Kinesiology/Obstetrics and Gynecology) and Jen Savage (Nutritional Sciences), Penn State University (1R01HL119245-01);
- Intervention components include dietary and physical activity (PA) education, individualized dietary and PA prescription, active learning, goal setting, and self monitoring (using records and PA monitors).
- The goal is to show the feasibility of an *adaptive, time-varying intervention* relying on control systems engineering concepts.
- Measures assessed daily, weekly, bi-weekly, or pre- and post-assessment.

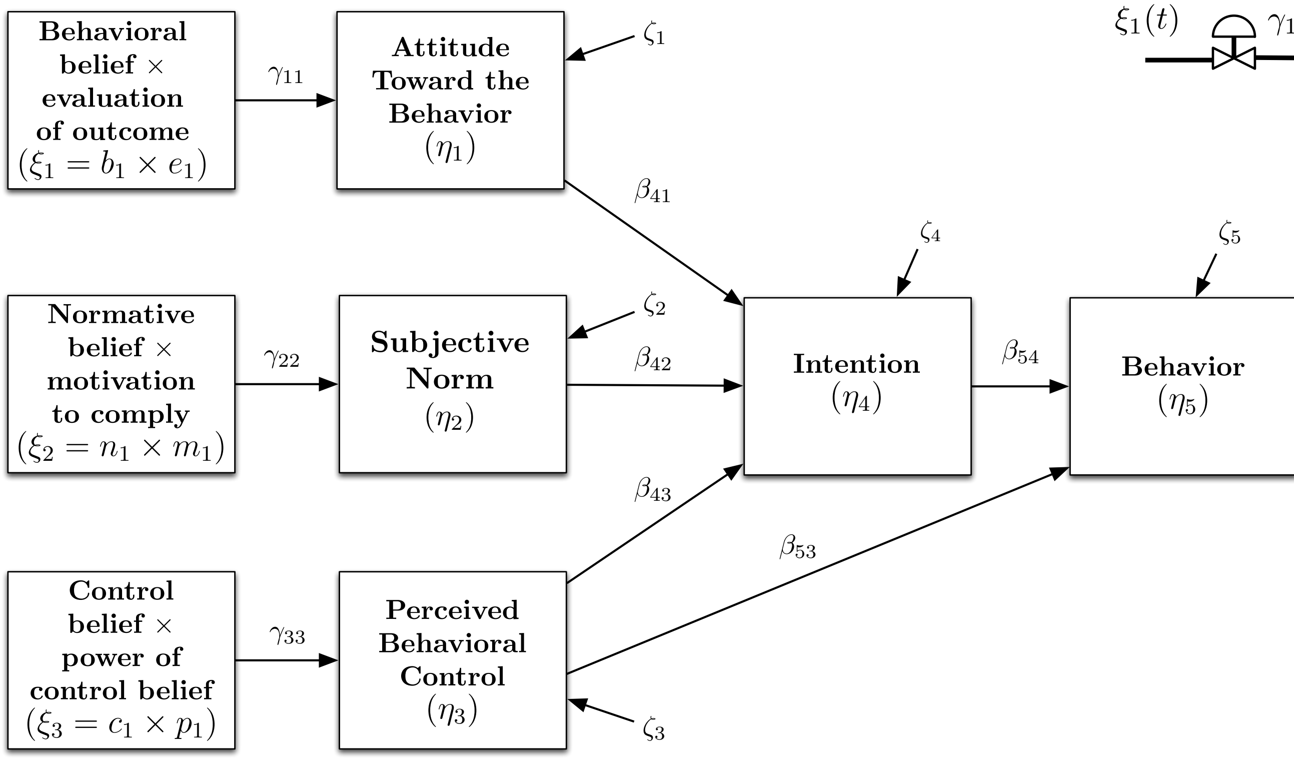
Overall Schematic Representation for the Adaptive GWG Intervention

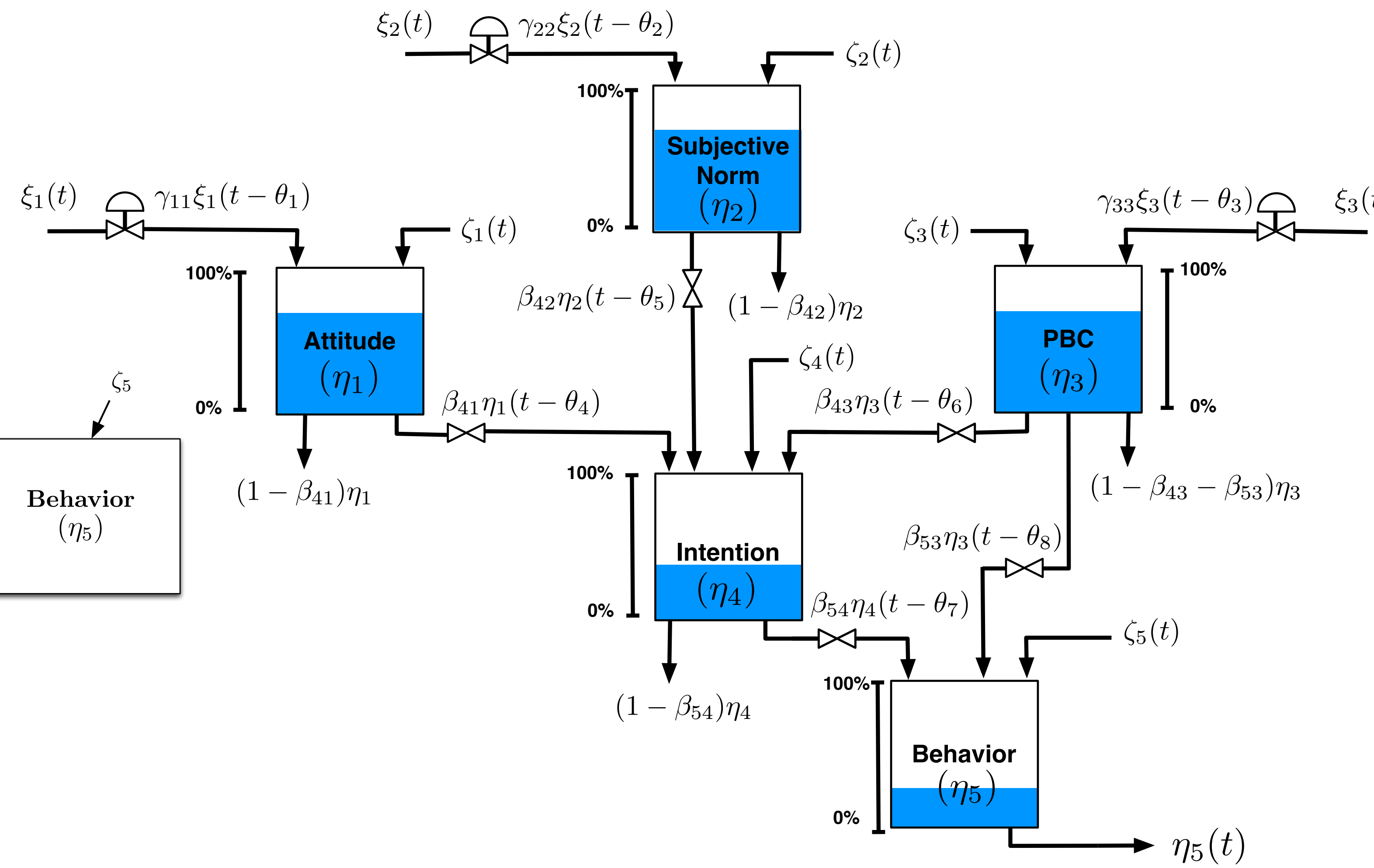


TPB ≡ Theory of Planned Behavior

Fluid Analogy for the Theory of Planned Behavior

Navarro-Barrientos, J.E., D.E. Rivera, and L.M. Collins, "A dynamical model for describing behavioural interventions for weight loss and body composition change," *Mathematical and Computer Modelling of Dynamical Systems*, Volume 17, No. 2, Pages 183-203, 2011.





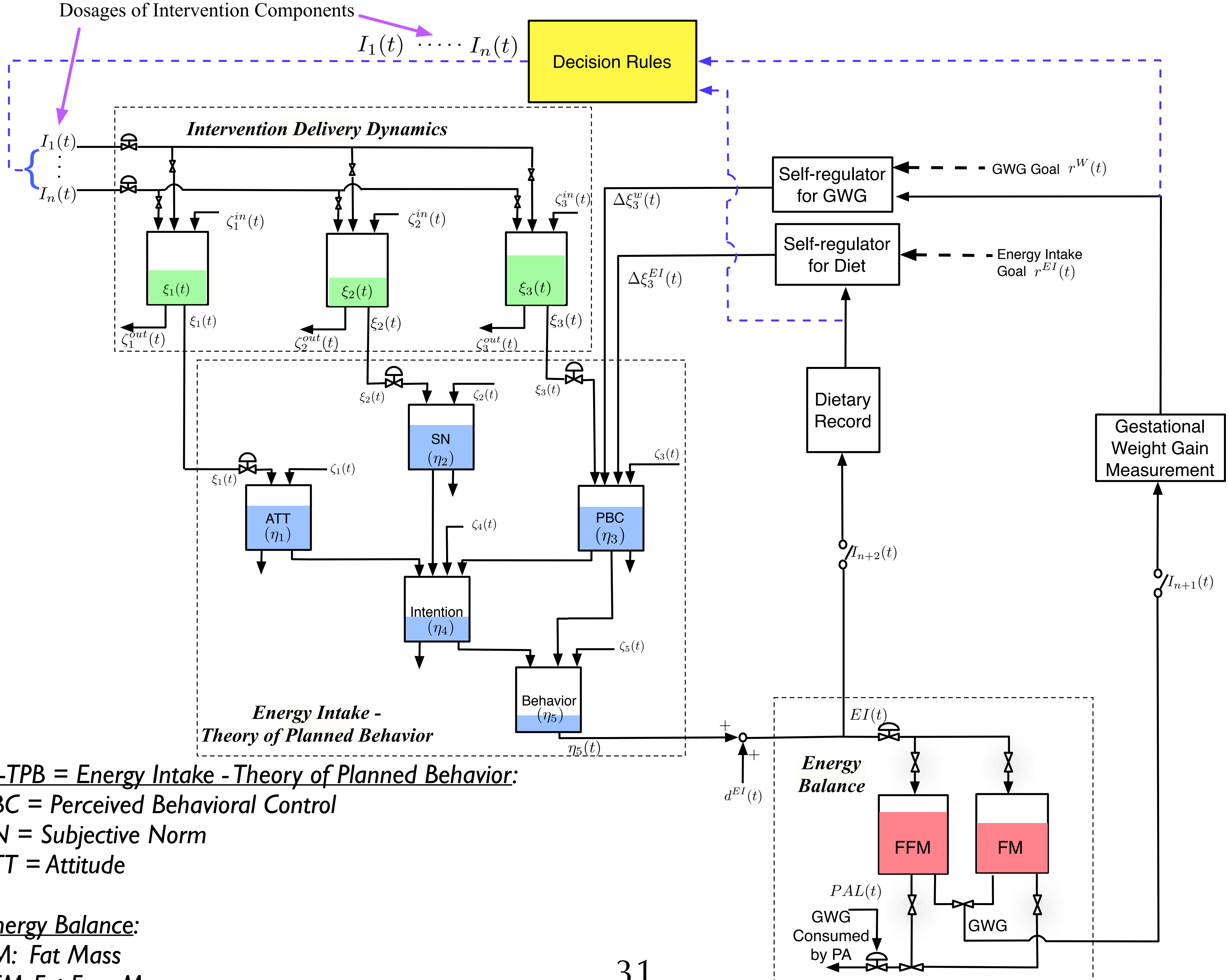
Any path diagram can be expressed into a corresponding fluid analogy described by a system of differential equations!

The conservation principle (Accumulation = Inflow − Outflow) leads to the following system of differential equations:

$$
\begin{aligned}
\tau_1 \frac{d\eta_1}{dt} &= \gamma_{11}\xi_1(t-\theta_1) - \eta_1(t) + \zeta_1(t) \\
\tau_2 \frac{d\eta_2}{dt} &= \gamma_{22}\xi_2(t-\theta_2) - \eta_2(t) + \zeta_2(t) \\
\tau_3 \frac{d\eta_3}{dt} &= \gamma_{33}\xi_3(t-\theta_3) - \eta_3(t) + \zeta_3(t) \\
\tau_4 \frac{d\eta_4}{dt} &= \beta_{41}\eta_1(t-\theta_4) + \beta_{42}\eta_2(t-\theta_5) + \beta_{43}\eta_3(t-\theta_6) - \eta_4(t) + \zeta_4(t) \\
\tau_5 \frac{d\eta_5}{dt} &= \beta_{54}\eta_4(t-\theta_7) + \beta_{53}\eta_3(t-\theta_8) - \eta_5(t) + \zeta_5(t),
\end{aligned}
$$

where:
$\tau_1, \cdots, \tau_5$ are time constants,
$\eta_1, \cdots, \eta_5$ are the inventories,
$\xi_1(t) = b_1(t)e_1(t)$, $\xi_2(t) = n_1(t)m_1(t)$, $\xi_3(t) = c_1(t)p_1(t)$,
$\gamma_{11}, \cdots, \gamma_{33}$ are the inflow resistances,
$\beta_{41}, \cdots, \beta_{54}$ are the outflow resistances,
$\theta_1, \cdots, \theta_7$ are time delays and $\zeta_1, \cdots, \zeta_5$ are disturbances.

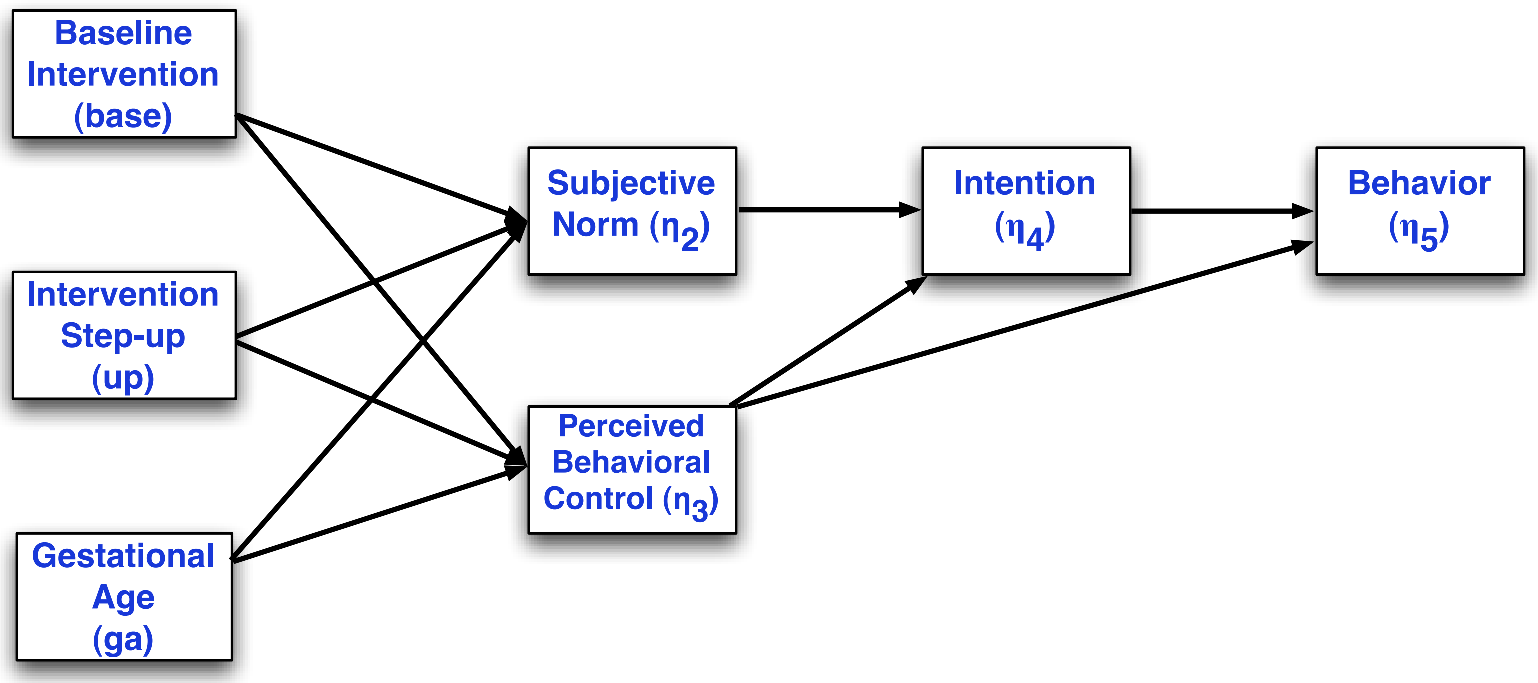
Closed Loop Illustration for GWG Intervention Fluid Analogy (Energy Intake)

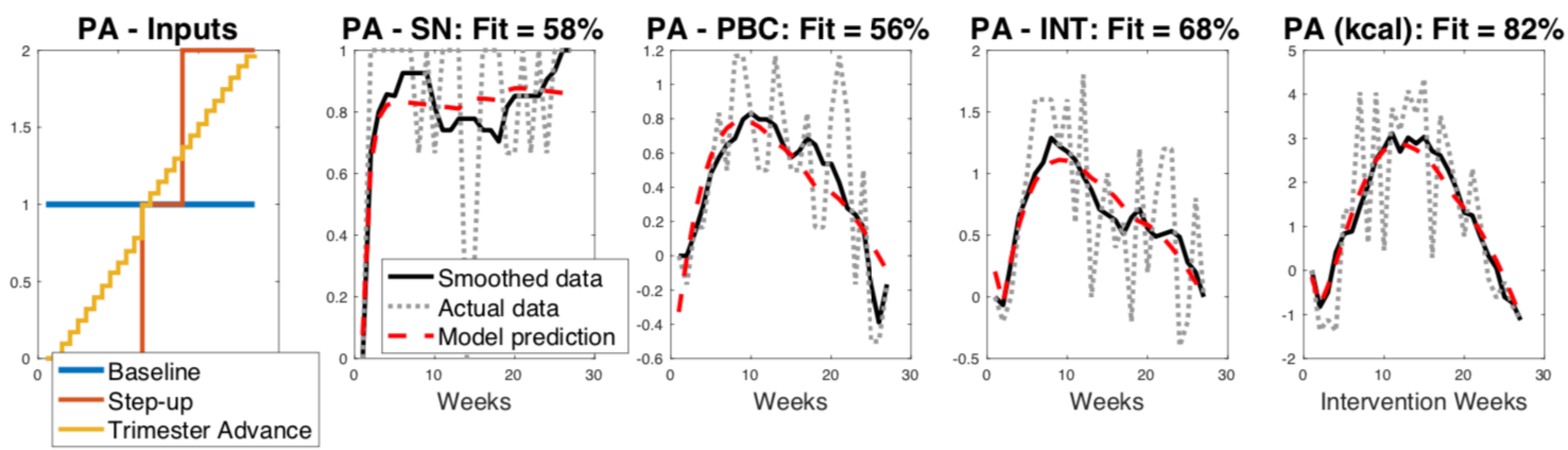


EI-TPB = Energy Intake - Theory of Planned Behavior:
PBC = Perceived Behavioral Control
SN = Subjective Norm
ATT = Attitude

Energy Balance:
FM: Fat Mass
FFM: Fat-Free Mass

HMZ TPB-PA Model Results (Phase 2 Participant)





- PA: Physical Activity

Social Cognitive Theory

SCT describes a behavioral change model in which individuals proactively self-reflect, self-regulate, and self-organize (Bandura, 1989).

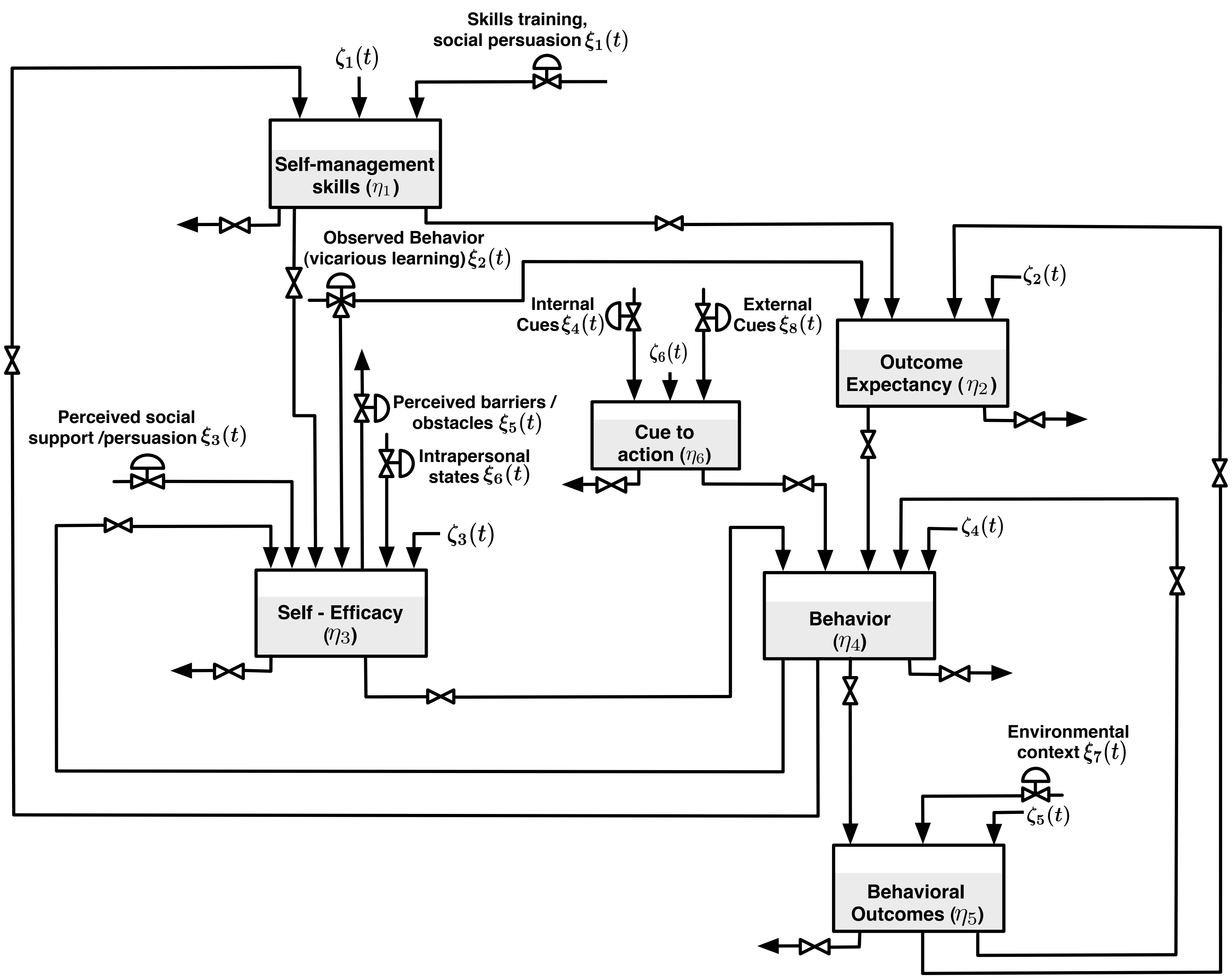
Selected SCT components that are generated as a consequence of variation of external or internal stimuli (outputs) are:

- *Self-efficacy* (e.g. perceived confidence in one's ability)
- *Behavioral outcomes* (e.g. weight loss, physical pain)
- *Behavior* (e.g. physical activity, days of abstinence, cigarettes per day).

Selected variables that act as stimuli to promote (or relegate) behavior and other components (inputs) are:

- *Skills training*
- *Observed behavior (vicarious learning)*
- *Environmental context*
- *Internal and external cues* (e.g. triggers to behavior)

Fluid Analogy for Social Cognitive Theory



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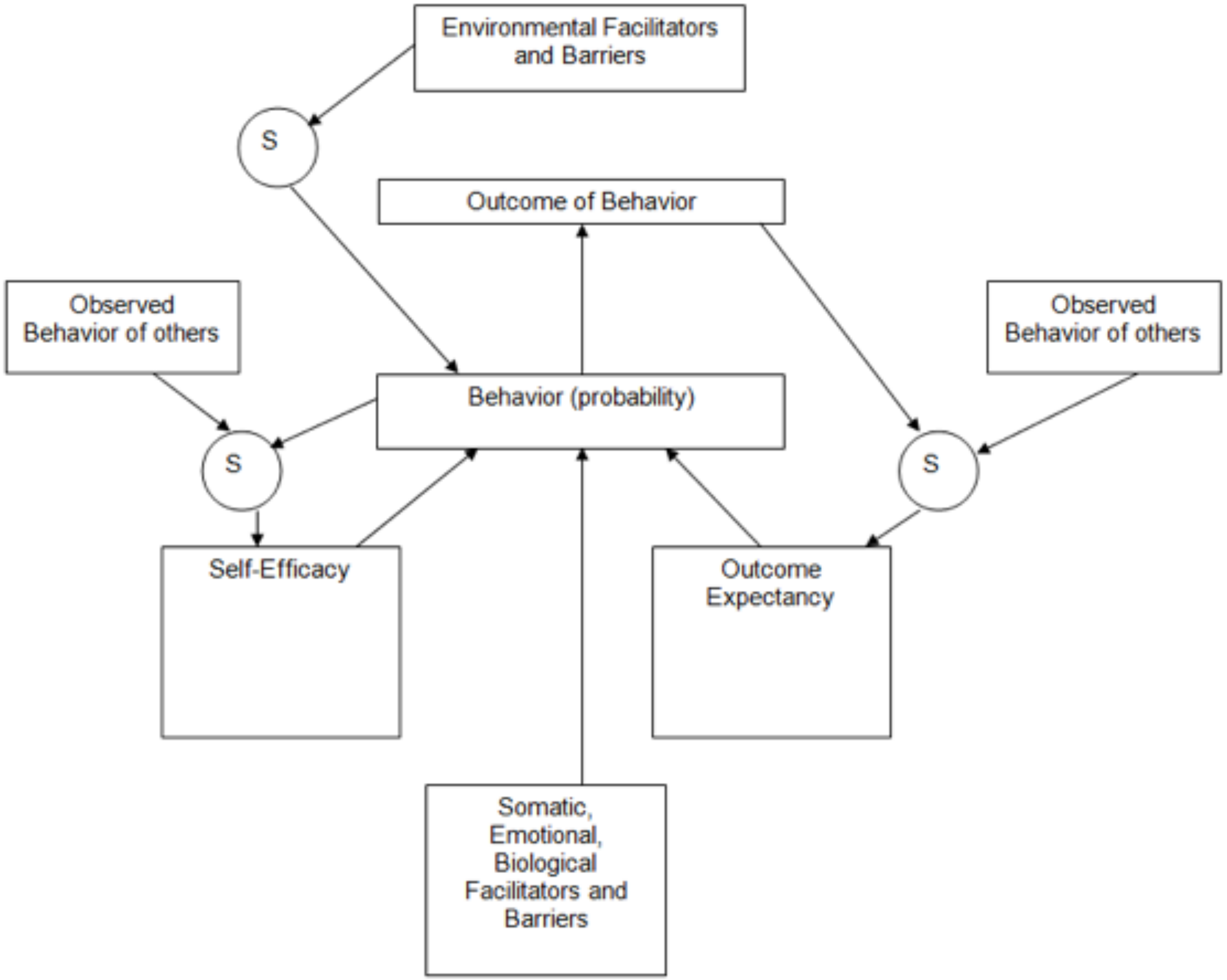
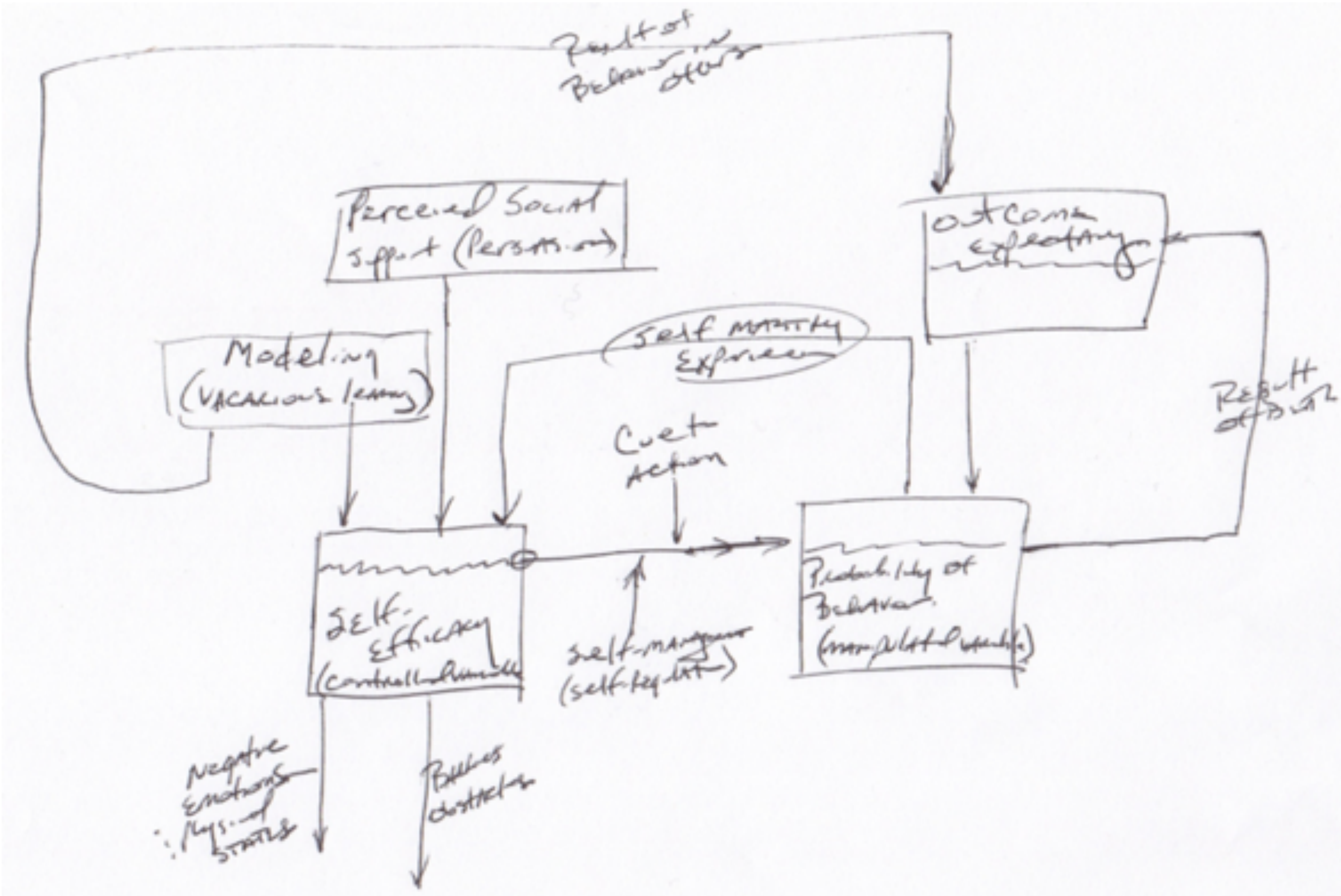
Initial Conceptual Diagram (W.T. Riley, 8/1/11)



Refined Fluid Analogy (W.T. Riley, 10/29/12)



SCT Path Diagram
(from fluid analogy, *TBM* paper)

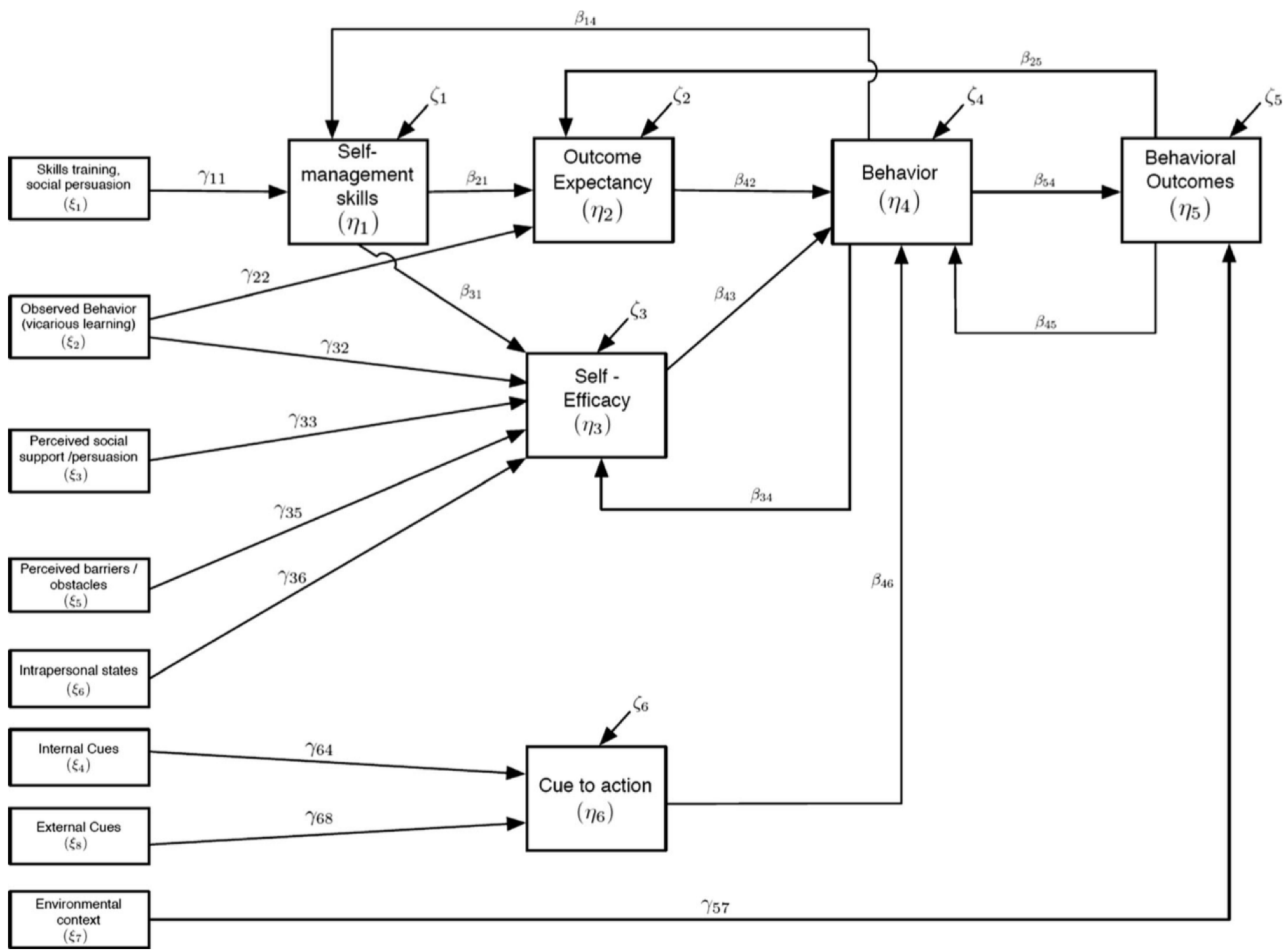
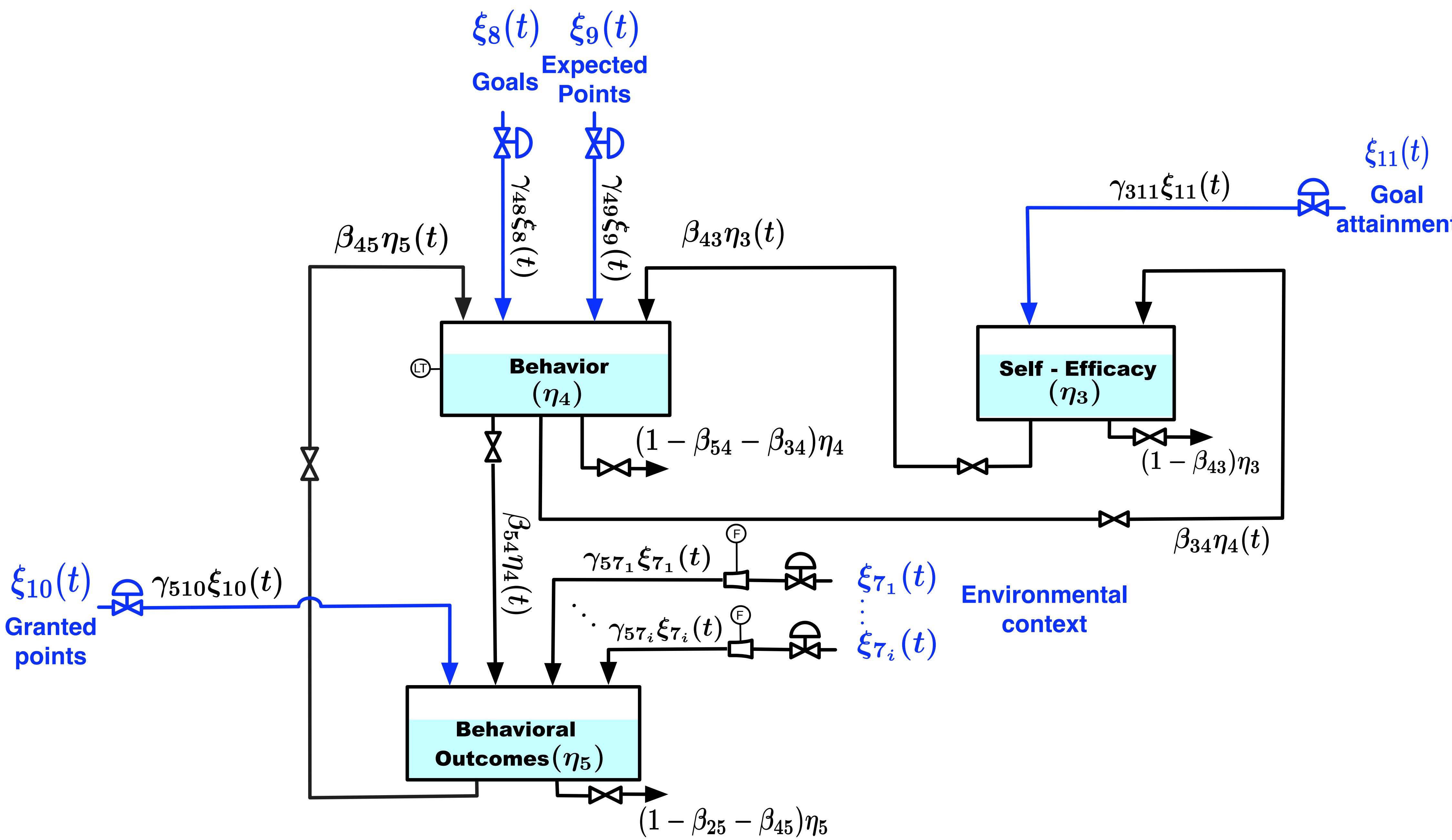


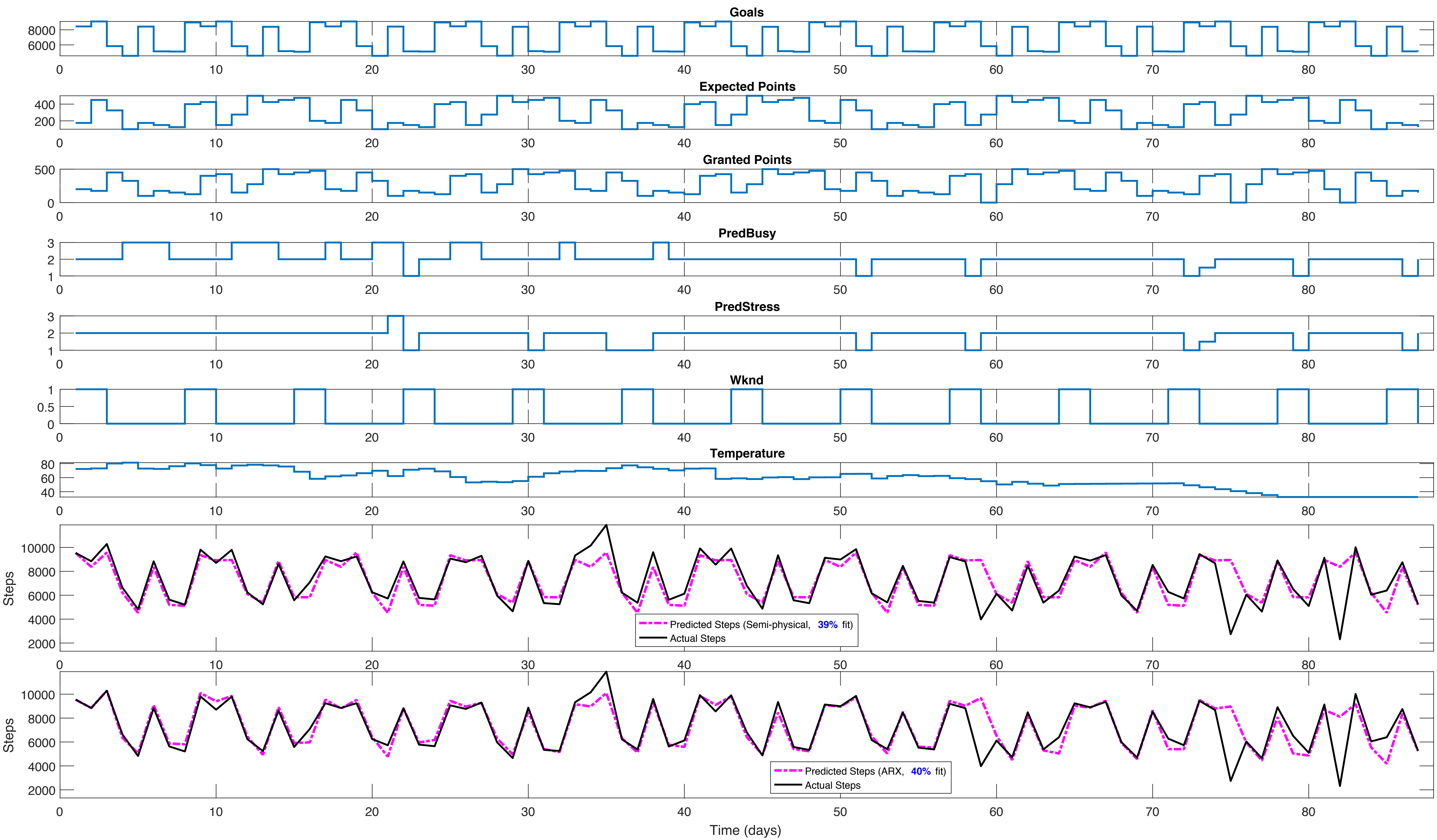
Fig. 3 | Path diagram of SCT based on fluid analogy in Fig. 1

Operant Learning (OL) - Self-Efficacy (SE) Reduced SCT Structure



- Relying on inputs determined important from black-box (ARX) modeling, examine a reduced, parsimonious SCT structure.

Participant "A"
(ARX 40% vs OL-SE 39% Fit Index)

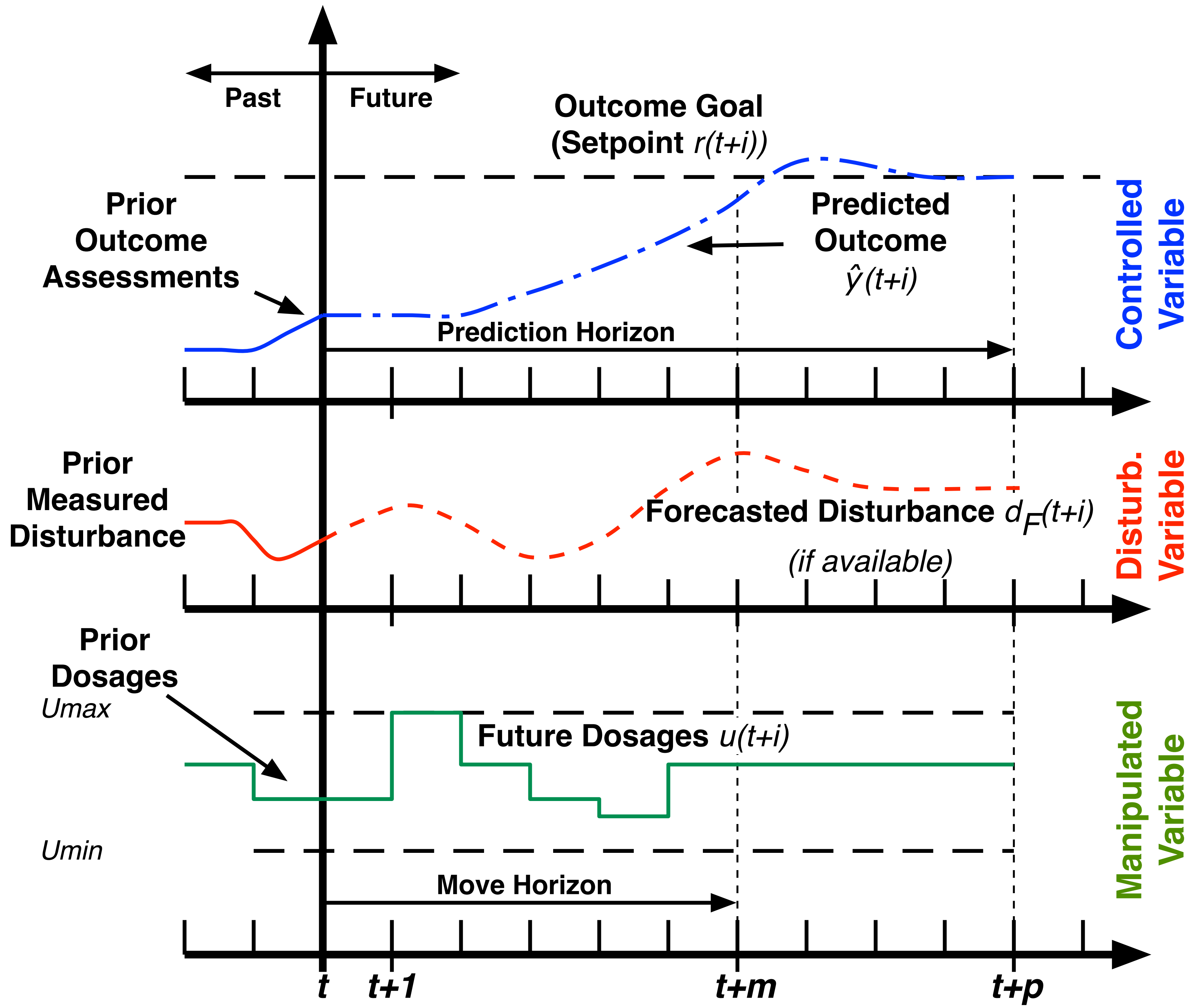


Controller Functional Requirements

The decision algorithm/“controller” must:

- consider multiple outcomes,
- decide on multiple intervention dosages,
- incorporate both *feedback* and *feedforward* decision-making,
- incorporate constraint handling,
- manage categorical (i.e., discrete-valued) dosages.

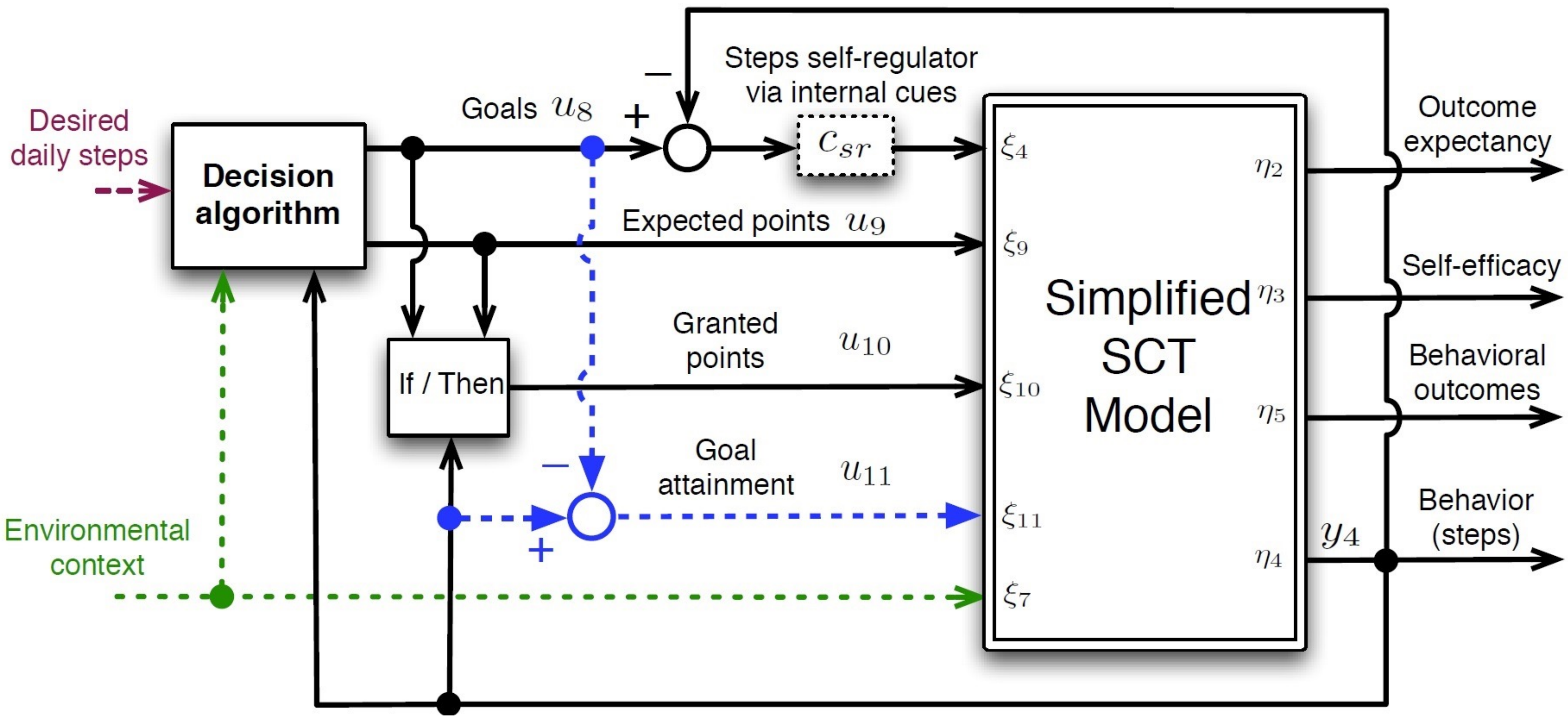
Model Predictive Control (MPC) Conceptual Representation



$$\min_{\Delta u(t)\ldots\Delta u(t+m-1)} J = \overbrace{\sum_{i=1}^{p} Q_e(i)(\hat{y}(t+i) - r(t+i))^2}^{\text{Take Tailoring Variables to Goal}} + \overbrace{\sum_{i=1}^{m} Q_{\Delta u}(i)(\Delta u(t+i-1))^2}^{\text{Penalize Changes in the Intervention Dosages}}$$

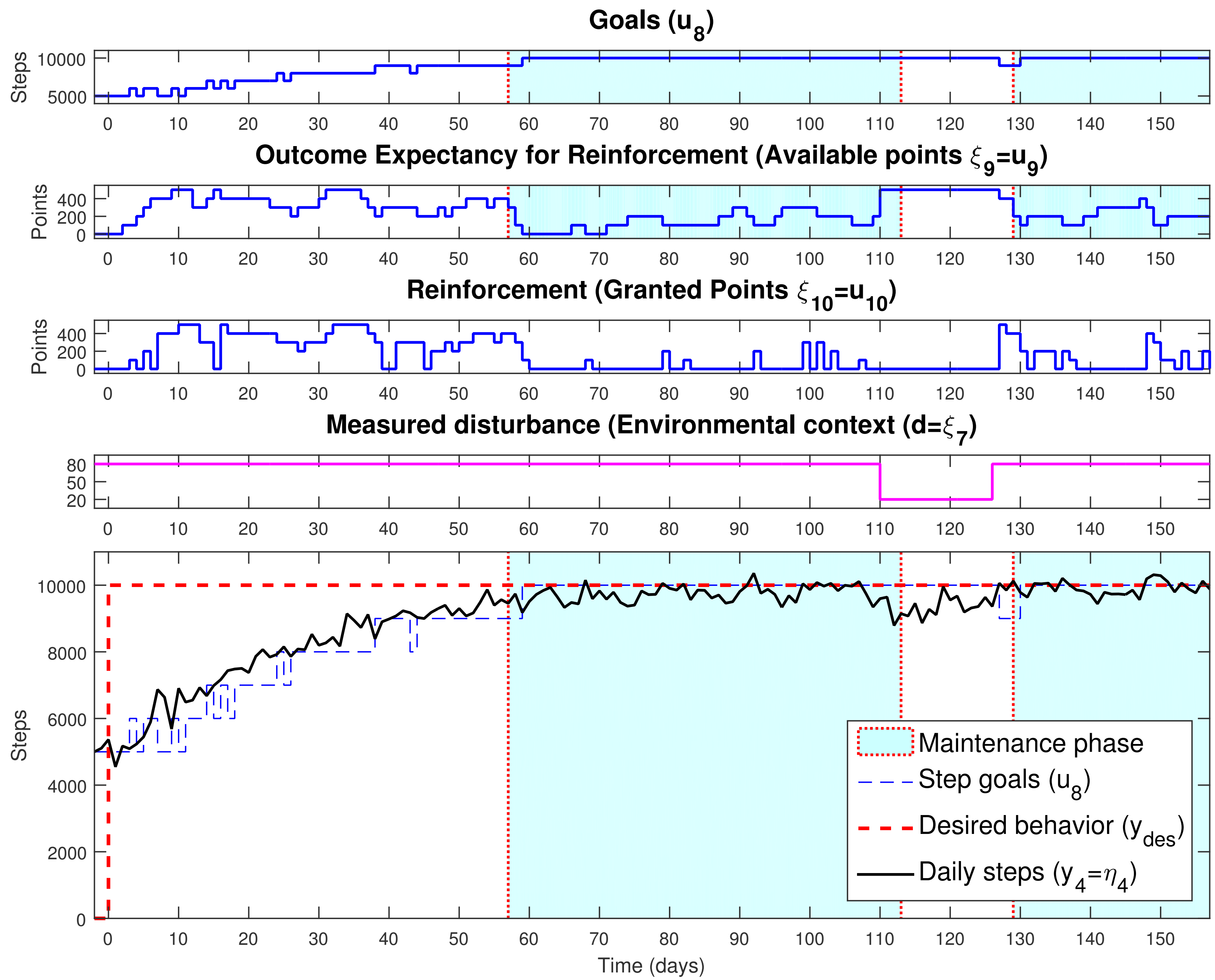
Closed-Loop Intervention

Conceptual representation of the closed-loop adaptive intervention, based on the simplified version of the SCT model; shows a subset of the measured/designed *Just Walk* signals.



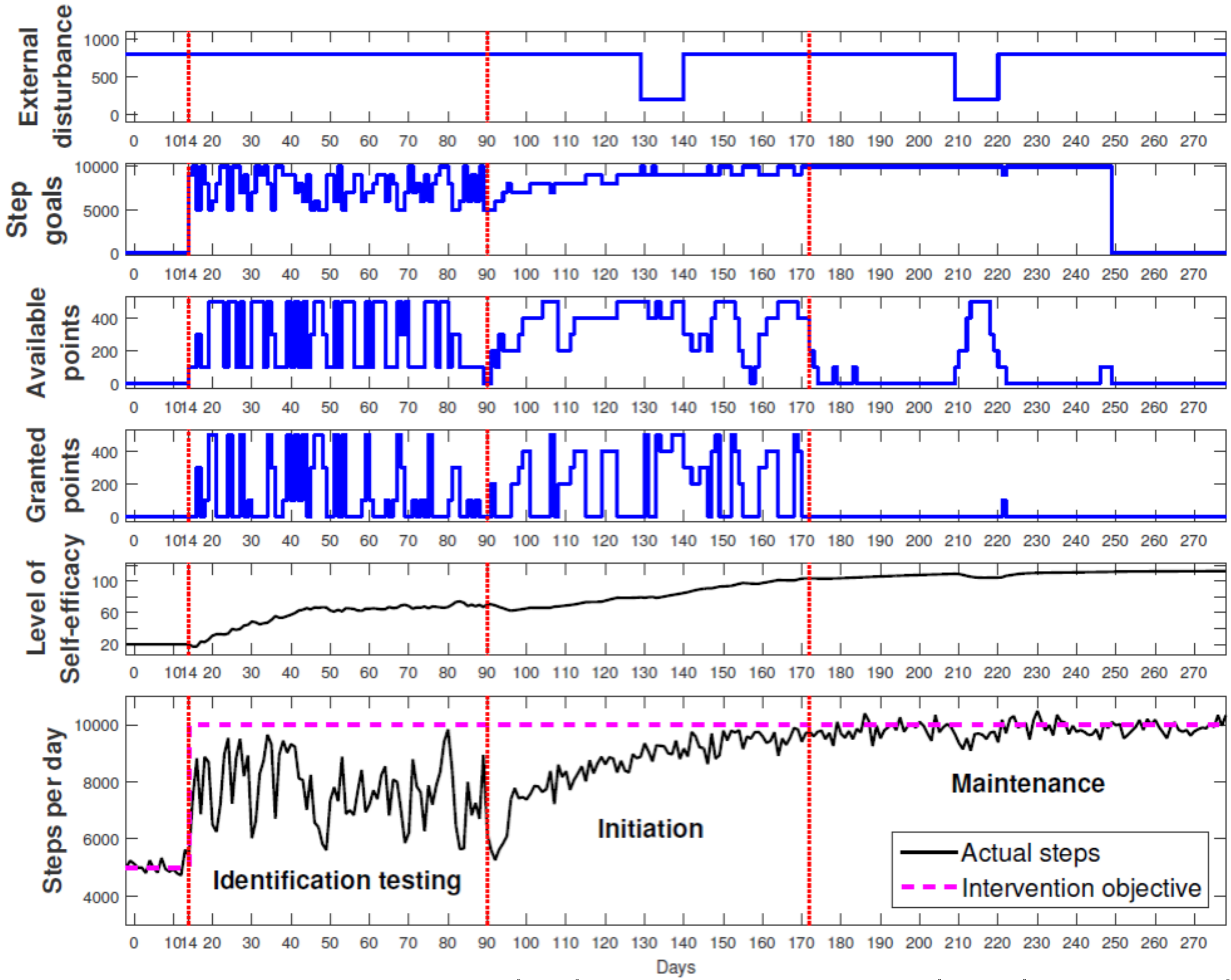
C. A. Martín, D. E. Rivera and E. B. Hekler, **A decision framework for an adaptive behavioral intervention for physical activity using hybrid model predictive control**, 2016 American Control Conference (ACC), Boston, MA, 2016, pp. 3576-3581.

Closed-Loop Intervention(includes Maintenance)



- HMPC algorithm is reconfigured during "maintenance" phases.

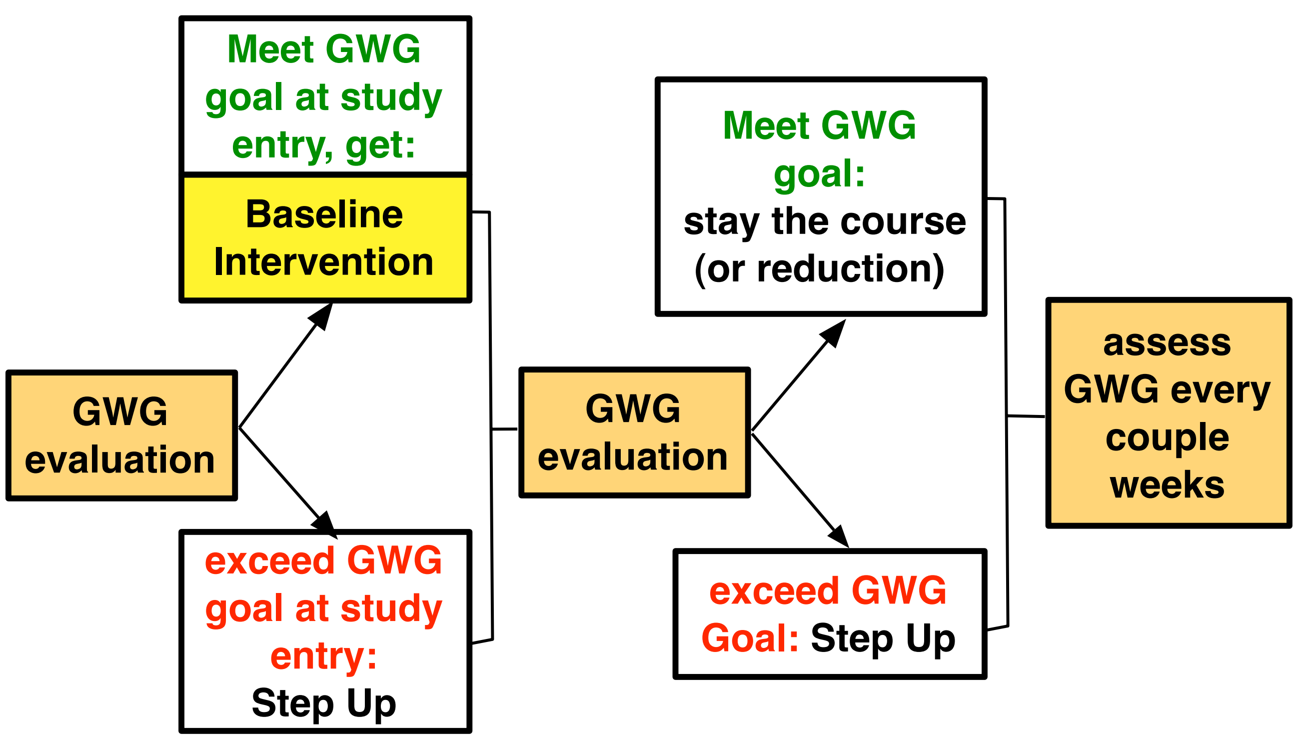
The Control Optimization Trial **(COT)**
Just Walk v2



Hekler E.B., D.E. Rivera, C.A., Martin, S.S. Phatak, M.T. Freigoun, E. Korinek, P. Klasnja, M.A. Adams and M.P. Buman. "Tutorial for using control systems engineering to optimize adaptive mobile health interventions." *J Med Internet Res*, 20(6):e214, (2018) DOI: 10.2196/jmir.8622.

Adaptive GWG Intervention: Decision Rule Illustration

- *Time-varying, adaptive* intervention via decision rules involving:
  - augmentation/reduction of components following a certain dosage sequence;
  - at each decision point, only one component can be adjusted.

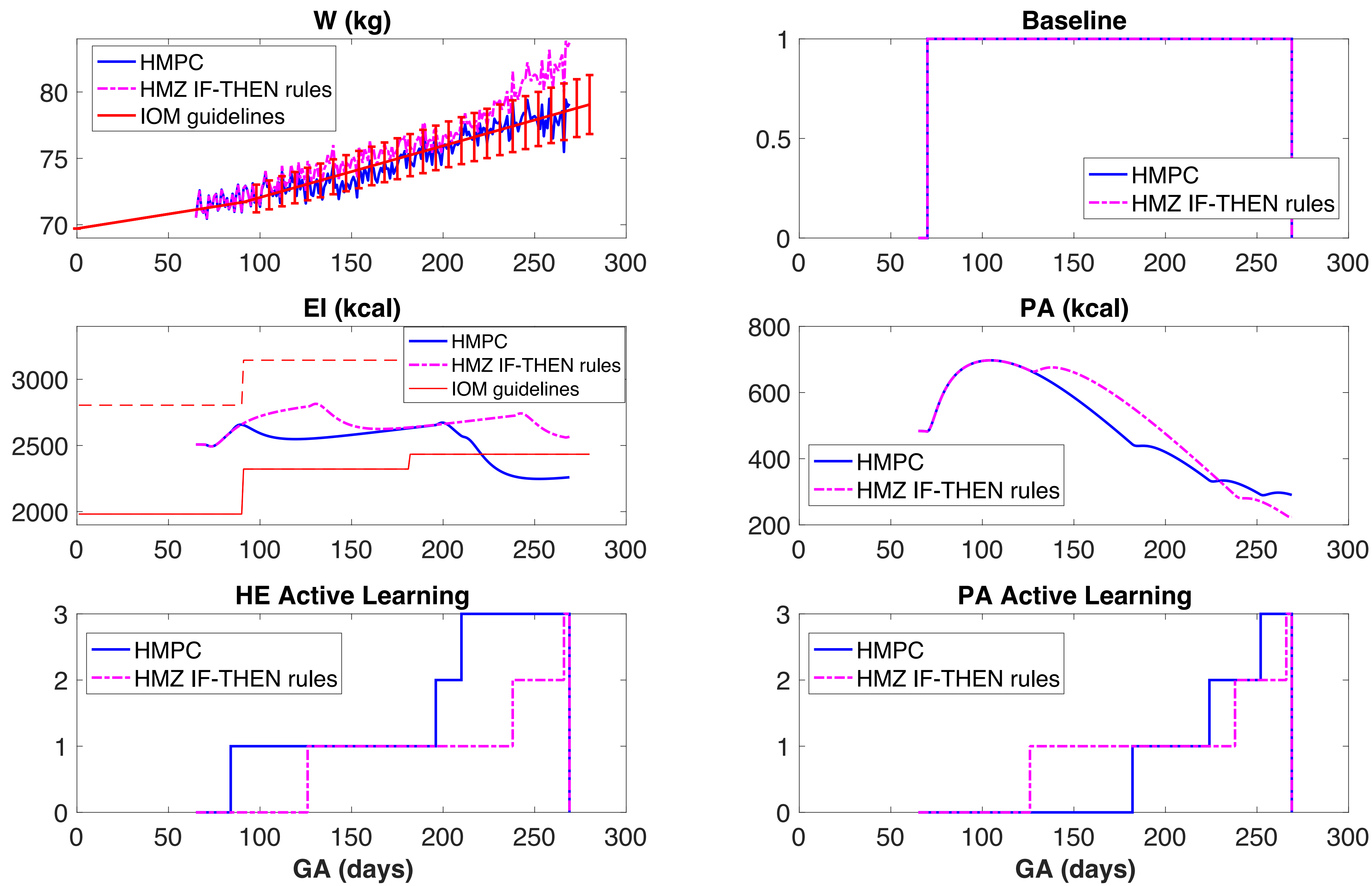


Options	Adaptation
Step down 3	reduction of goal setting
Step down 2	reduction of HE component*
Step down 1	reduction of PA component#
Baseline	Base Dosage for all components
Step up 1	1st augmentation of HE component
Step up 2	2nd augmentation of HE component
Step up 3	1st augmentation of PA component
Step up 4	2nd augmentation of PA component
Step up 5	3rd augmentation of PA component

* HE component: Healthy Eating Active Learning
\# PA component: Physical Activity Active Learning

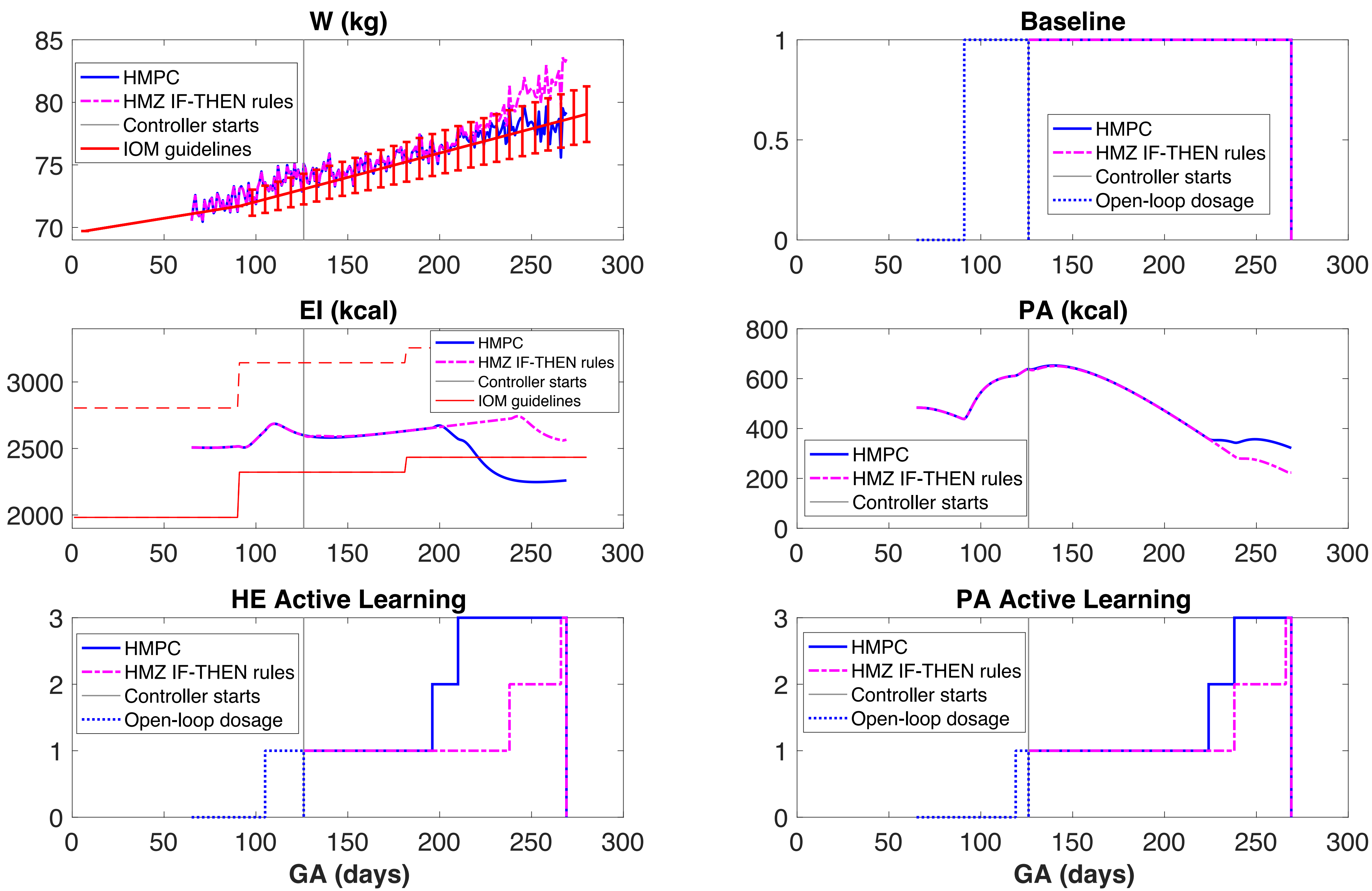
Dong, Y., D. E. Rivera, D. S. Downs, J. S. Savage, D. M. Thomas, and L. M. Collins "Hybrid model predictive control for optimizing gestational weight gain behavioral interventions" *Proceedings of the 2013 American Control Conference*, Washington, DC, pages:1973-1978.

HMZ Hybrid MPC Simulation
(using participant-validated model)



- MPC algorithm anticipates the need for dosage augmentations, because of its improved understanding of participant response as a result of the dynamical system model.

HMZ Control Optimization Trial Simulation (using participant-validated model)



- In the open-loop portion of the COT, augmentations in HE and PA active learning provide data from which a dynamical system model is obtained.

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COT Future Plans

- The COT will be evaluated experimentally in *Just Walk* v2, which is being developed in fulfillment of the aims of R01CA244777.

- Clinical trial with $N = 386$ is planned; a myriad of activities (involving tech development, measurement, model development, clinical trails, recruitment and meaningful consent) are involved.

- An iterative, intelligent triangulation process is needed to achieve success.

How does this relate to machine learning?

- Machine learning is a very broad field, associated with many tasks beyond decision rules (e.g., classification, detection, etc.)
- Reinforcement learning is probably the closest parallel to control systems engineering; no "hostilities" exist between fields, just different perspectives and points of view.
- Benefits afforded in control systems engineering through:
  - use of behavioral theory to help define model structure.
  - experimental design (using multisines or step changes) to improve model accuracy and reliability.
  - controller robustness (through tuning) means that models need not be perfect to meet requirements.

Summary and Concluding Thoughts

- mHealth behavioral interventions represent an interesting (though challenging) class of control engineering applications, with significant impact on public health.

- Control systems engineering informs the design of decision "rules" and model development for optimized adaptive interventions.

- Behavioral theories allow "physics" to be part of the problem. Their use is a distinctive aspect of the control engineering approach.

- Aspirational goal is to establish the *control optimization trial* (COT) as a reliable means to build "perpetually adaptive" closed-loop *mHealth* interventions; this is the basis for *Just Walk v2*.

Acknowledgments

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Thank you for your attention!

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