Methods: Mind the Gap Webinar Series

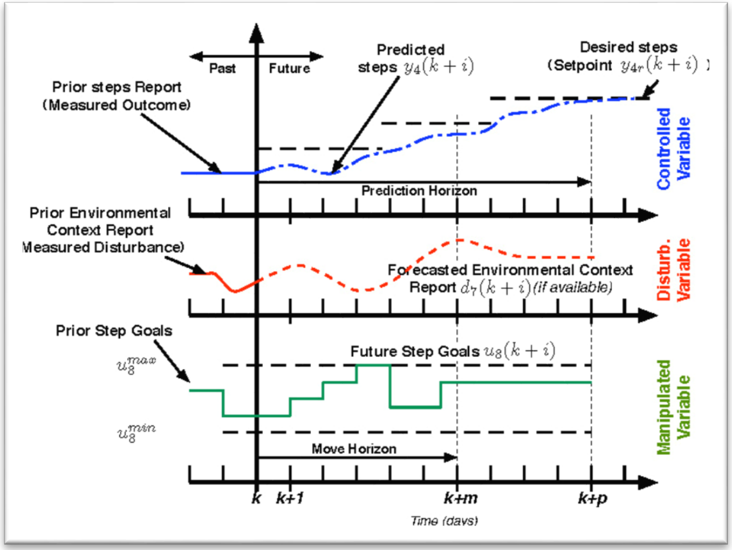
Using Control Systems Engineering to Optimize Adaptive Mobile Health Interventions

Presented by

Eric Hekler, Ph.D.

University of California, San Diego

Using Control Systems Engineering to Optimize Adaptive Mobile Health Interventions



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Just Walk “modeling and more” team

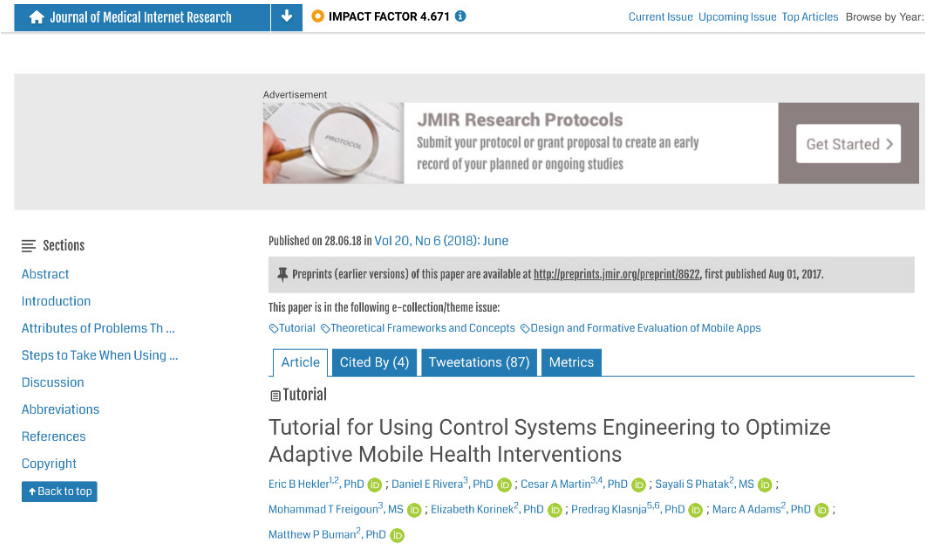
Everything changes and nothing stands still.
('Change is the only constant.')
-Heraclitus

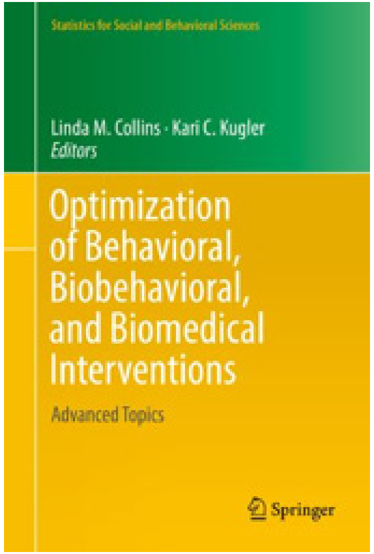
Take-home points

- If reducing lapses/relapses or promoting maintenance/abstinence is your goal, then a control optimization trial (COT) might help you.

- It’s not easy, but it’s easier than you think.

Key references





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Linda M. Collins
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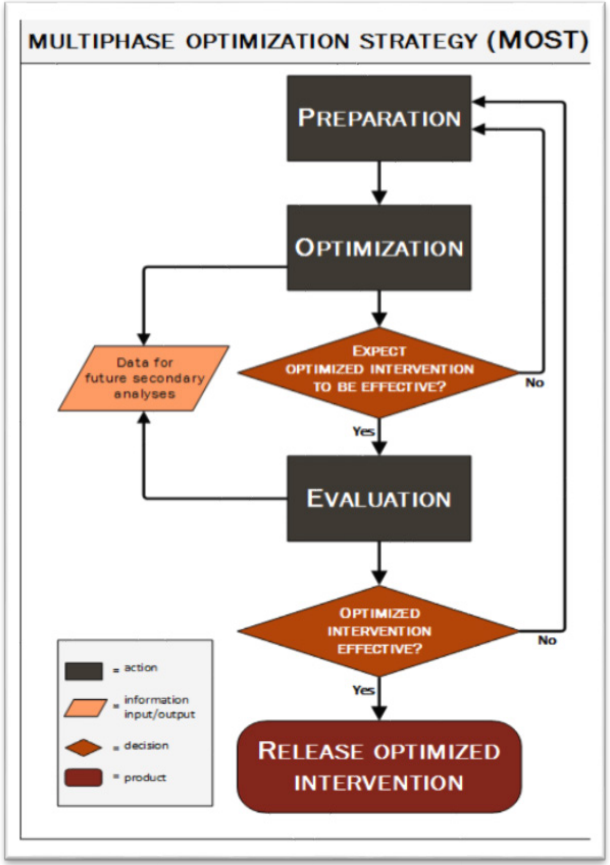

Collins & Krueger (2018) [Optimization of behavioral, biobehavioral, and biomedical interventions]

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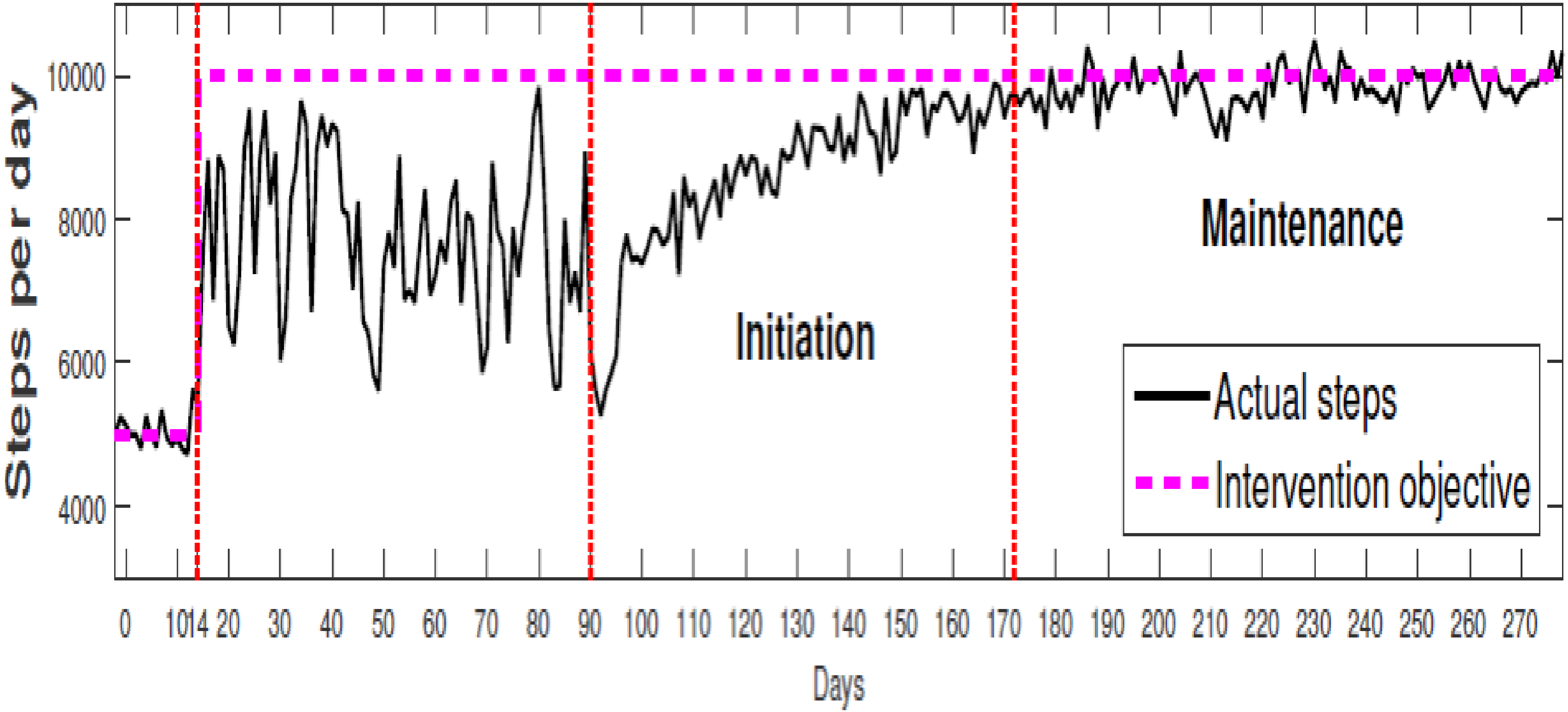
methodology.psu.edu

What can be optimized?

- Intervention package
  - Factorial/fractional factorial trial (FT)
- Infrequent, key decision rules (e.g., clinical practice)
  - Sequential Multiple Assignment Randomized Trial (SMART)
- Bout-specific decision rules (i.e., just-in-time adaptive interventions; JITAIs)
  - Micro-randomization Trials (MRTs)
- Gradual, non-linear, idiosyncratic change
  - Control Optimization Trial (COT)

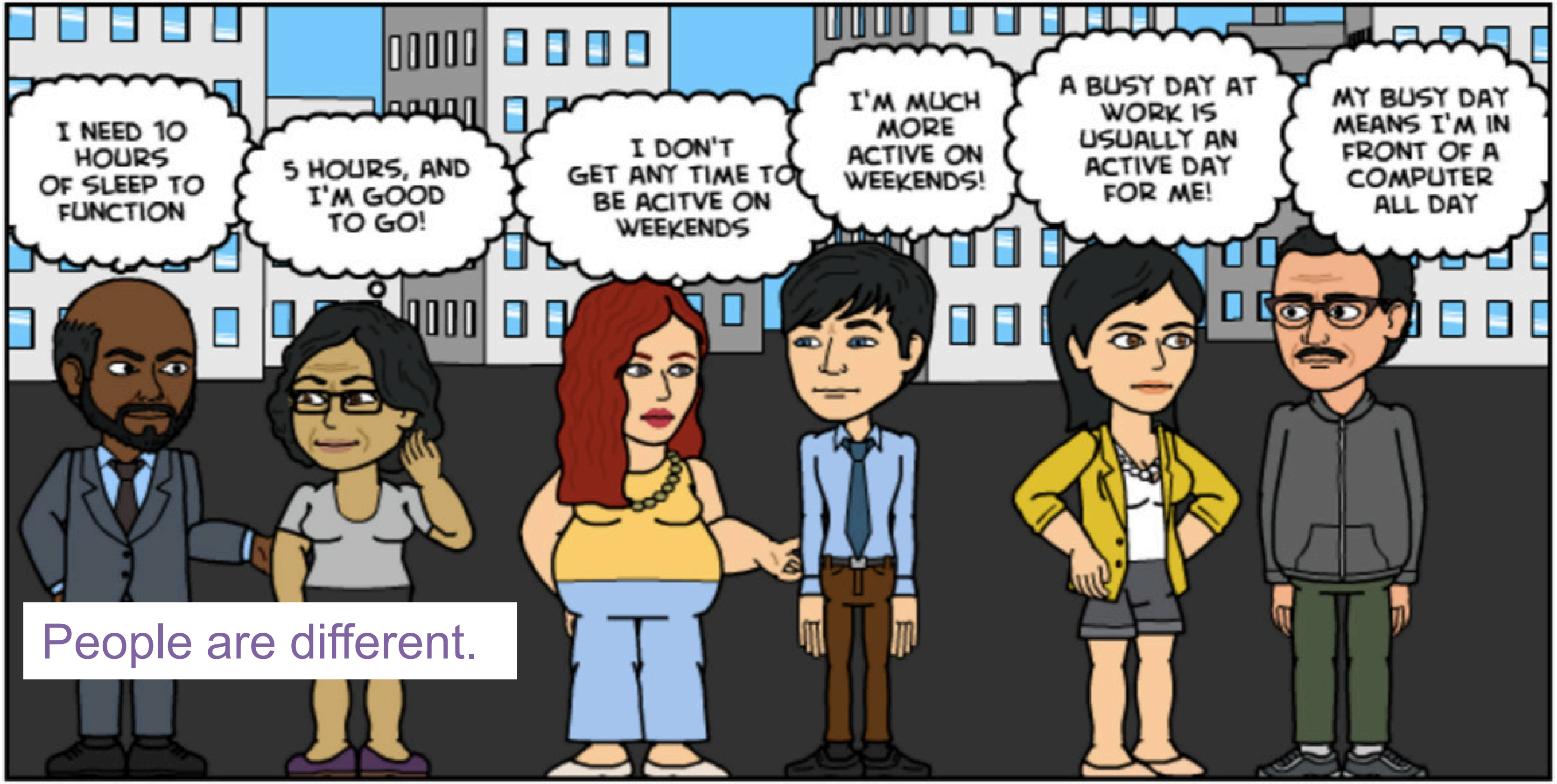
Gradual, non-linear, idiosyncratic change



How to optimize?

- Review of evidence from optimization trials <u>from prior participants</u>
  - FT, SMART, MRT, & COT
- "Real-time" optimization algorithm <u>for current individual</u>
  - MRT+ Reinforcement Learning (RL)
  - COT
    - Individualized & perpetually adapting

Need for individualized and perpetually adapting interventions

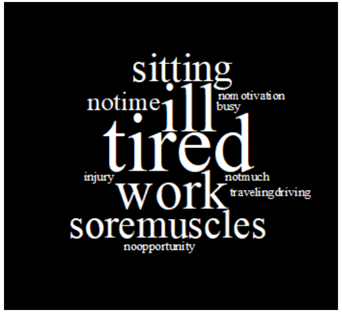


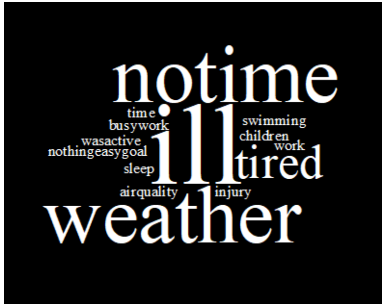
People are different.

Slide courtesy of @phataksayali

Need for <u>individualized</u> and <u>perpetually adapting</u> interventions

Reasons people offered via EMA on why they did not meet a daily step goal





People are different.

Context matters.

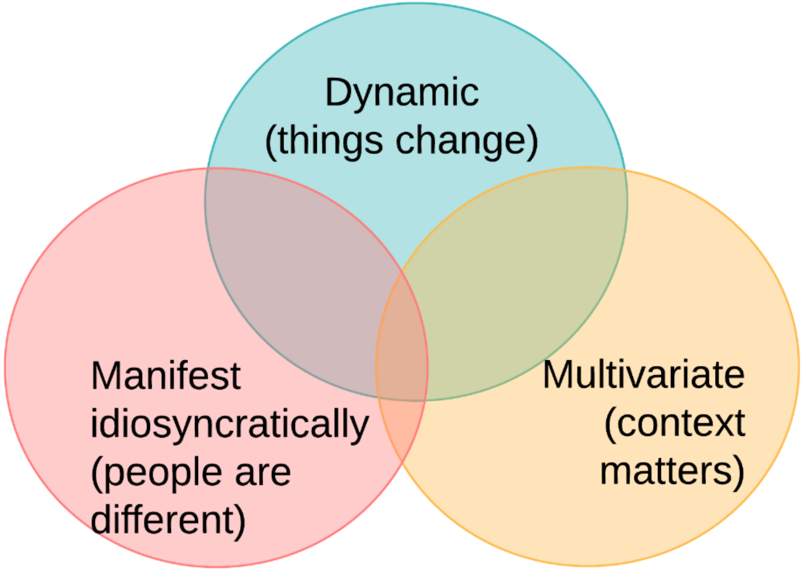
Slide adapted from @phataksayali

Everything changes and nothing stands still.
(Paraphrased into ‘change is the only constant.’)
-Heraclitus

People are different. Context matters. Things change.

Why use a real-time optimization algorithm?

- Inherent complexity of a problem

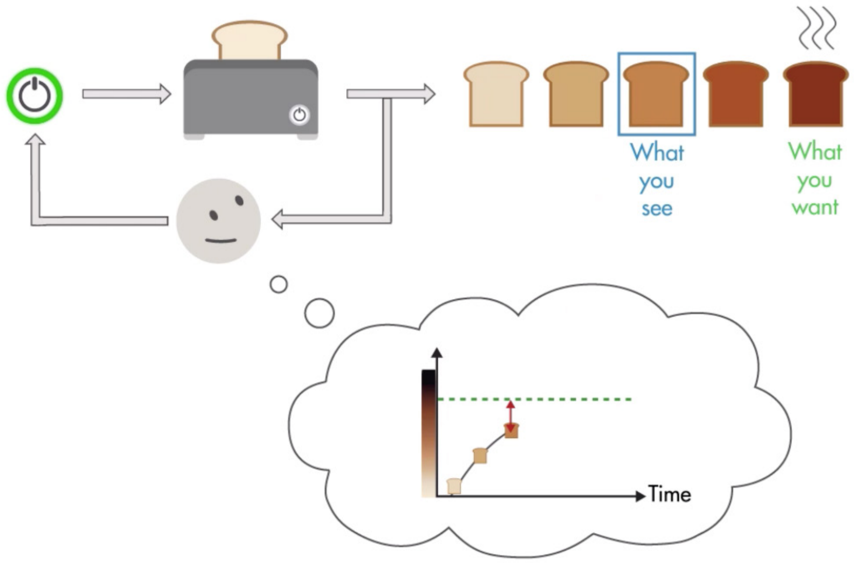


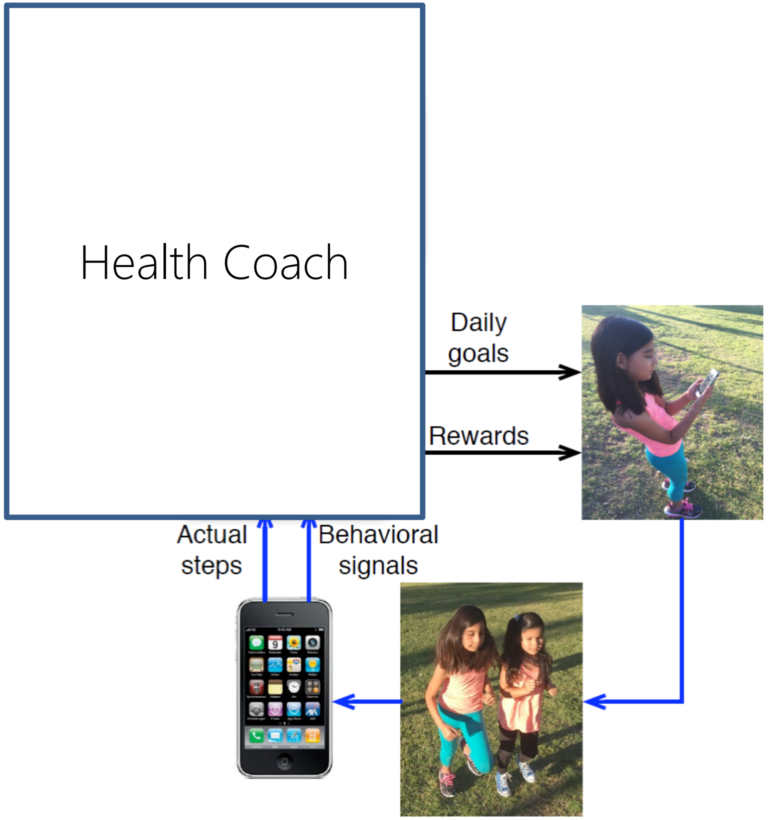
- Examples of complex problems
- From non-active to maintaining physical activity guidelines
- From obese to maintaining a normal weight
- From smoking to maintaining abstinence
- From depressed to maintaining good mental health

Control Systems Engineering

NSF IIS-1449751: EAGER: Defining a Dynamical Behavioral
Model to Support a Just in Time Adaptive Intervention, PIs, Hekler & Rivera
Hekler et al, JMIR 2018

How a controller works

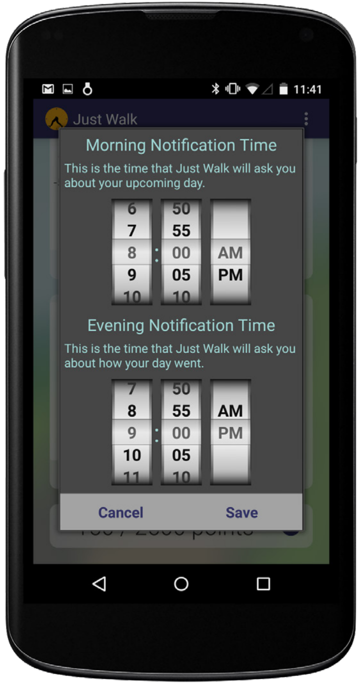


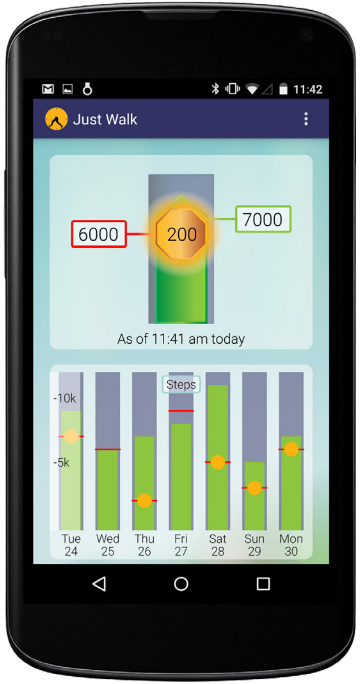


https://www.mathworks.com/videos/understanding-control-systems-part-2-feedback-control-systems-123501.html

C. A. Martín, D. E. Rivera and E. B. Hekler, *(2016) American Control Conference (ACC)*

Just Walk App





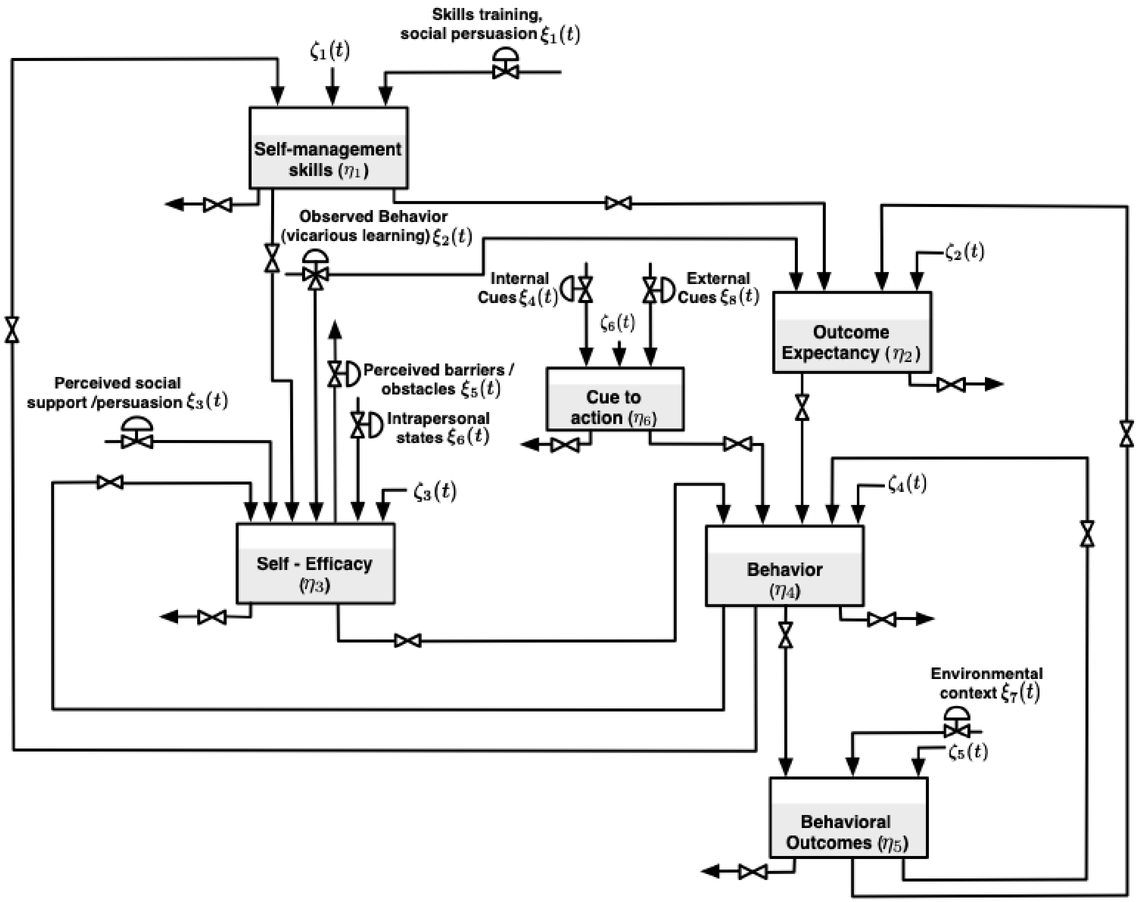
Normal intervention development steps

- Lit review - organize your understanding of prior work
- Define a hypothesis
- Test your hypothesis in naturalistic setting
  - e.g., observational trial/EMA trial
- Design your intervention
- Test your intervention

Step 1. Derive a dynamical model (organize prior work)

- Select/specify a general theoretical model
- Translate that into a dynamical model
- Vet dynamical model via simulation studies, secondary data analyses, or both.

Step 1: Derive a dynamical model

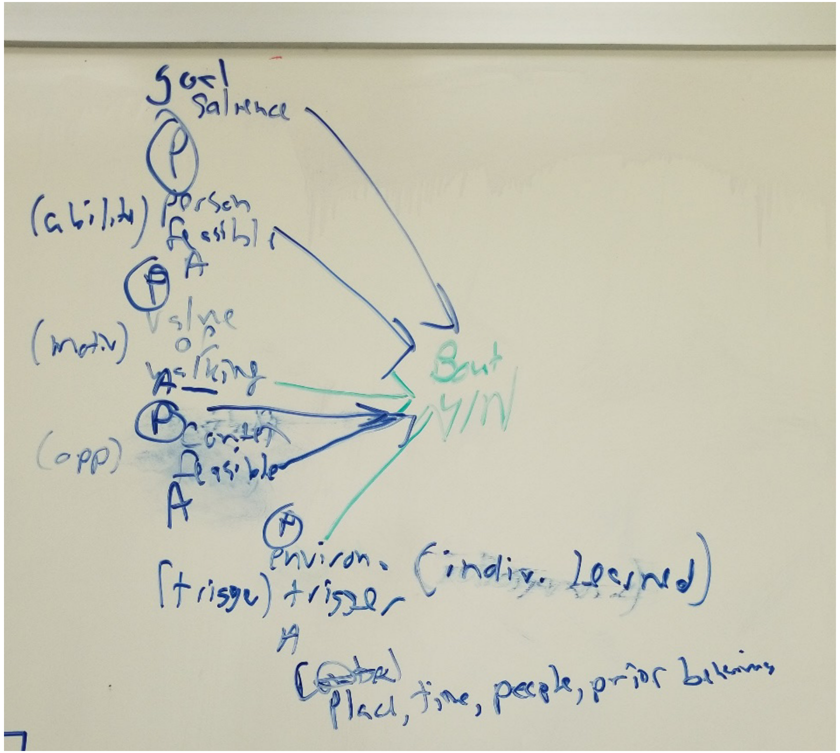


@ehekler

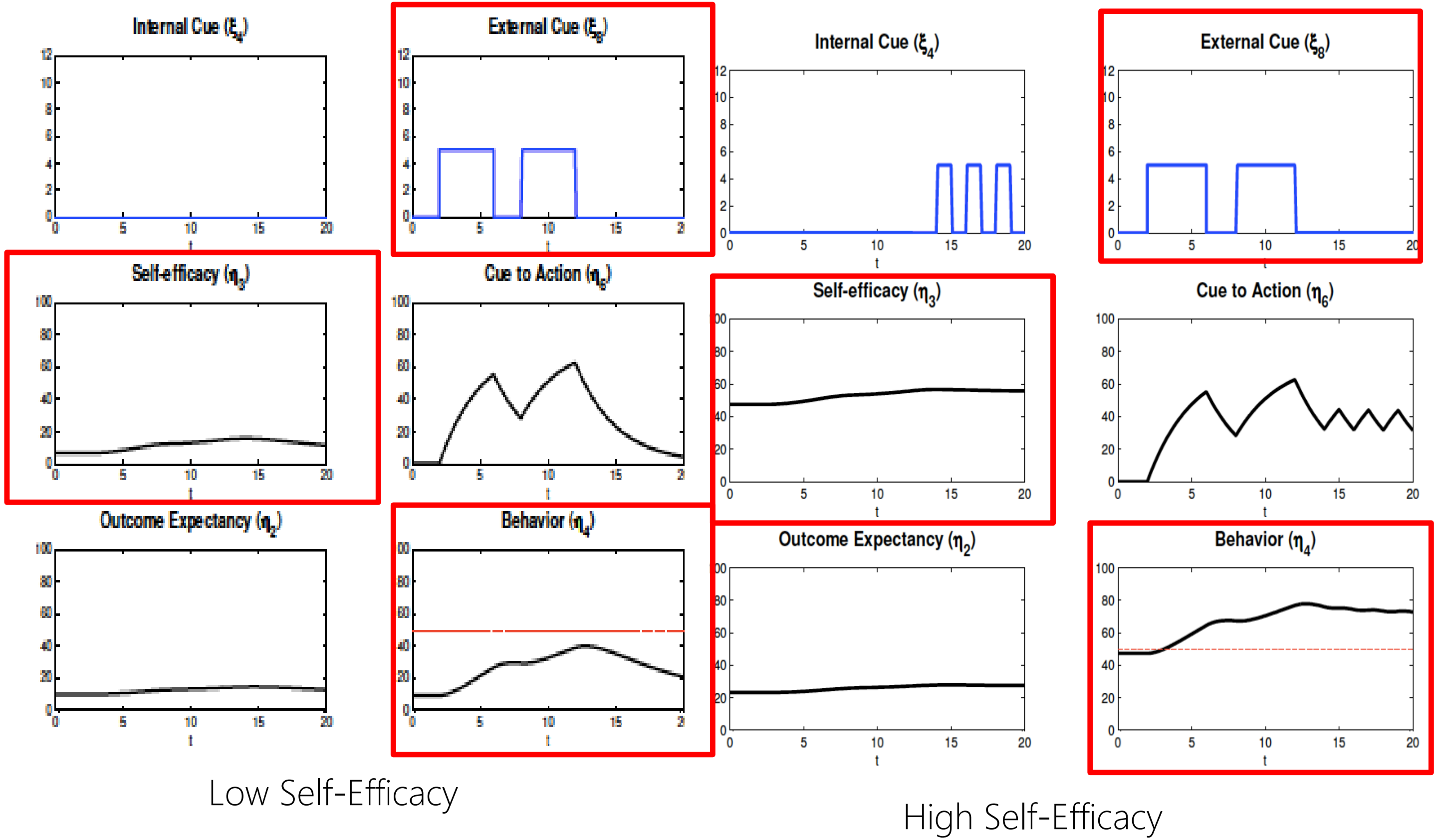
Martin, Hekler, Rivera, et al. (2018); Riley, Martin, Rivera, Hekler, et al. 2016; Martin, Riley, Rivera, Hekler, et al. 2014

It’s easier than you think…

- Many models have now been specified
  - SCT, TPB, etc
- Drawing on a whiteboard gets you pretty far
- You can find a control systems engineer partner
  - It’s a huge field! They are at your university.
  - Use our papers as a bridge

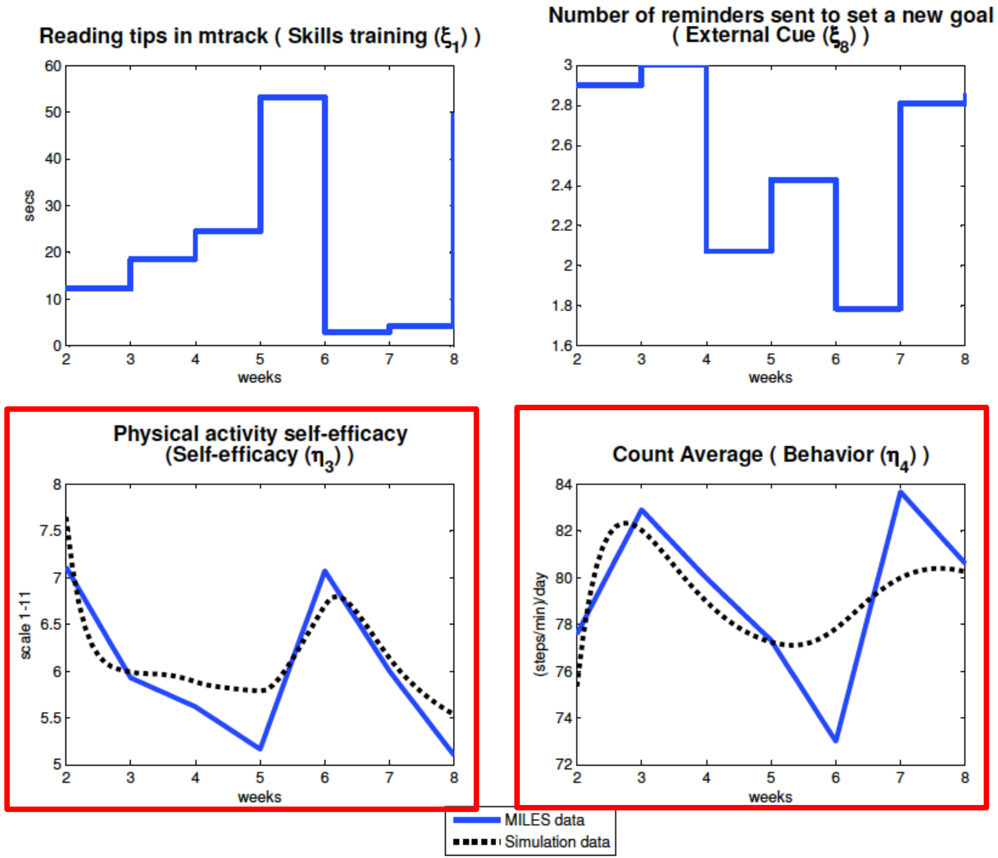


Step 1 (optional): test via simulation



Riley, Martin, Rivera, Hekler, et al. 2016; Martin, Riley, Rivera, Hekler, et al. 2014

Step 1 (optional): test via secondary analyses



Riley, Martin, Rivera, Hekler, et al. 2016; Martin, Riley, Rivera, Hekler, et al. 2014

Normal intervention development steps

- Lit review - organize your understanding of prior work
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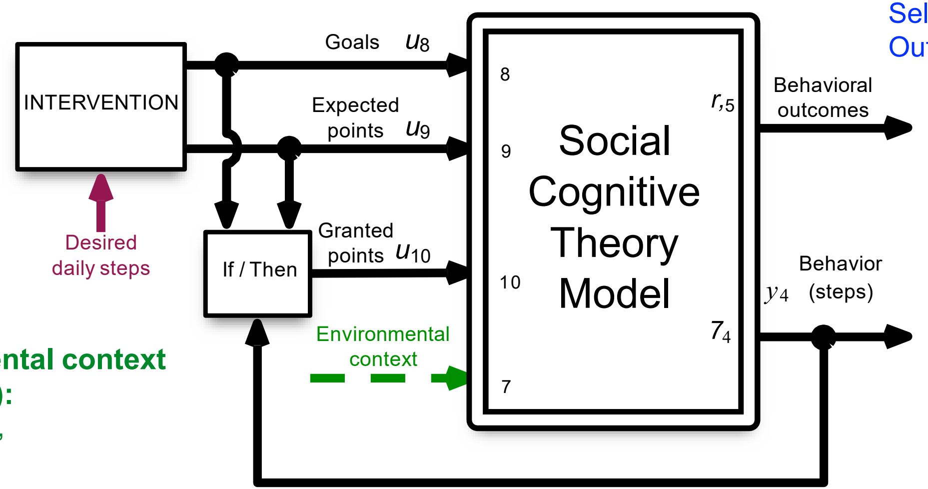
- Design your intervention
- Test your intervention

Step 2: Define intervention options and outcomes
(Define a hypothesis)

The intervention seeks to promote **physical activity (e.g., steps/day)** 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

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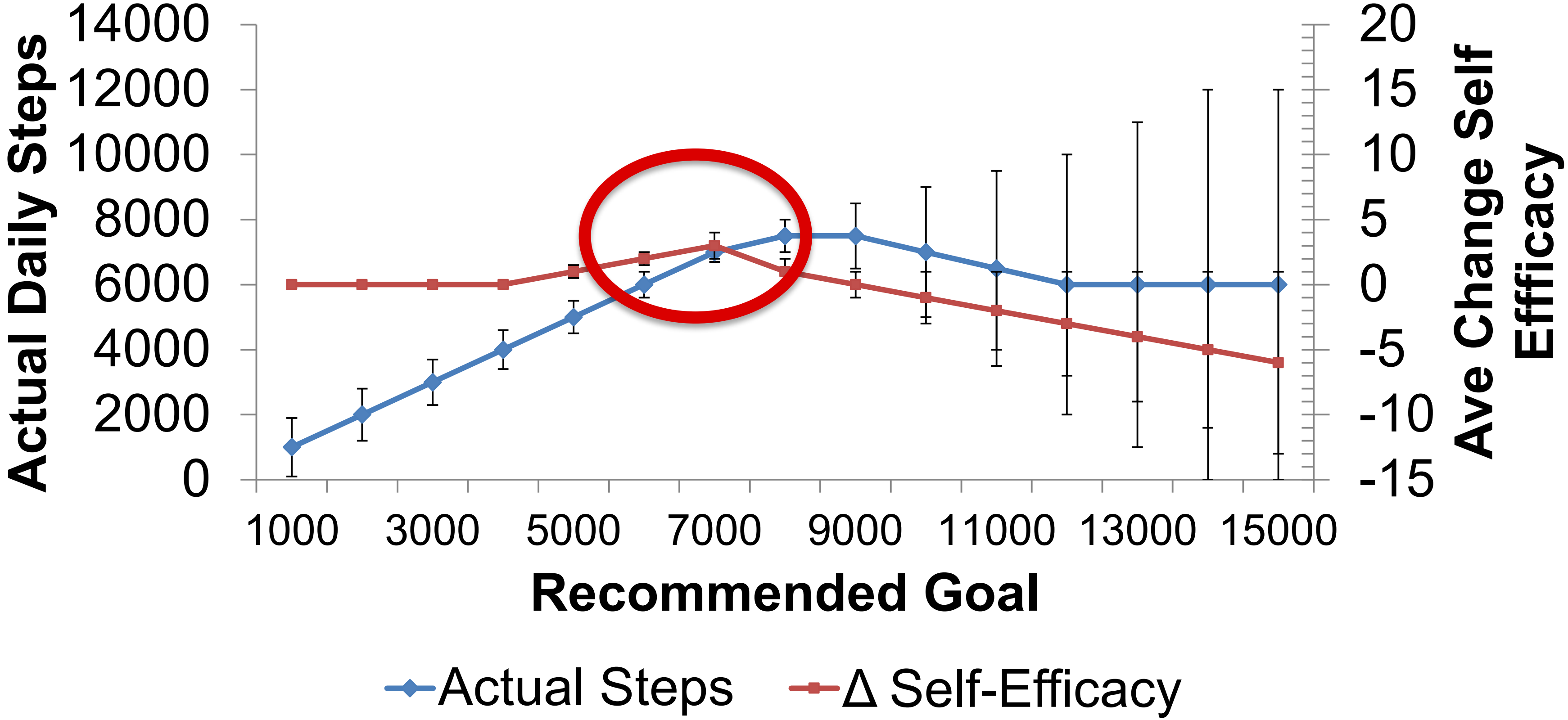
Martin, Rivera, & Hekler, 2015; 2016, American Control Conference

Step 2: Define intervention options and outcomes:

Daily "ambitious but doable" step goals



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Hekler (PI), Rivera (Co-PI), NSF IIS-1449751

Normal intervention development steps

- Lit review - organize your understanding of prior work
- Define a hypothesis
- Test your hypothesis in naturalistic setting
  - e.g., observational trial/EMA trial
- Design your intervention
- Test your intervention

"…to find out what happens when you change something it is necessary to change it."

-Box, Hunter, and Hunter (*Statistics for Experimenters*)

Step 3: Conduct a system ID experiment (test in natural setting)

- Design open loop system ID study and analytic plan
- Conduct data analyses

System identification (ID)

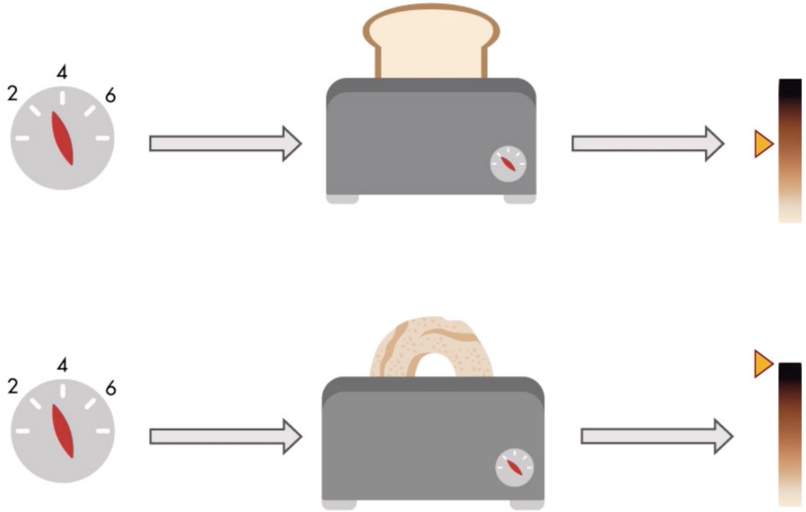
- System ID focuses on modeling of dynamical systems (such as humans) from data, ideally from experimentation, not merely observation.

- It is focused on <u>estimating/validating a model</u> to describe the system (e.g., a human).

- It is <u>NOT focused on effect size estimates</u> of intervention components.

One key COT sub-experiment

- Open loop system ID



Tests understanding of the "system"

a) theory-testing

b) individualized tailoring variable selection

@ehekler https://www.mathworks.com/videos/understanding-control-systems-part-1-open-loop-control-systems-123419.html

Step 3: Open loop system ID experiment

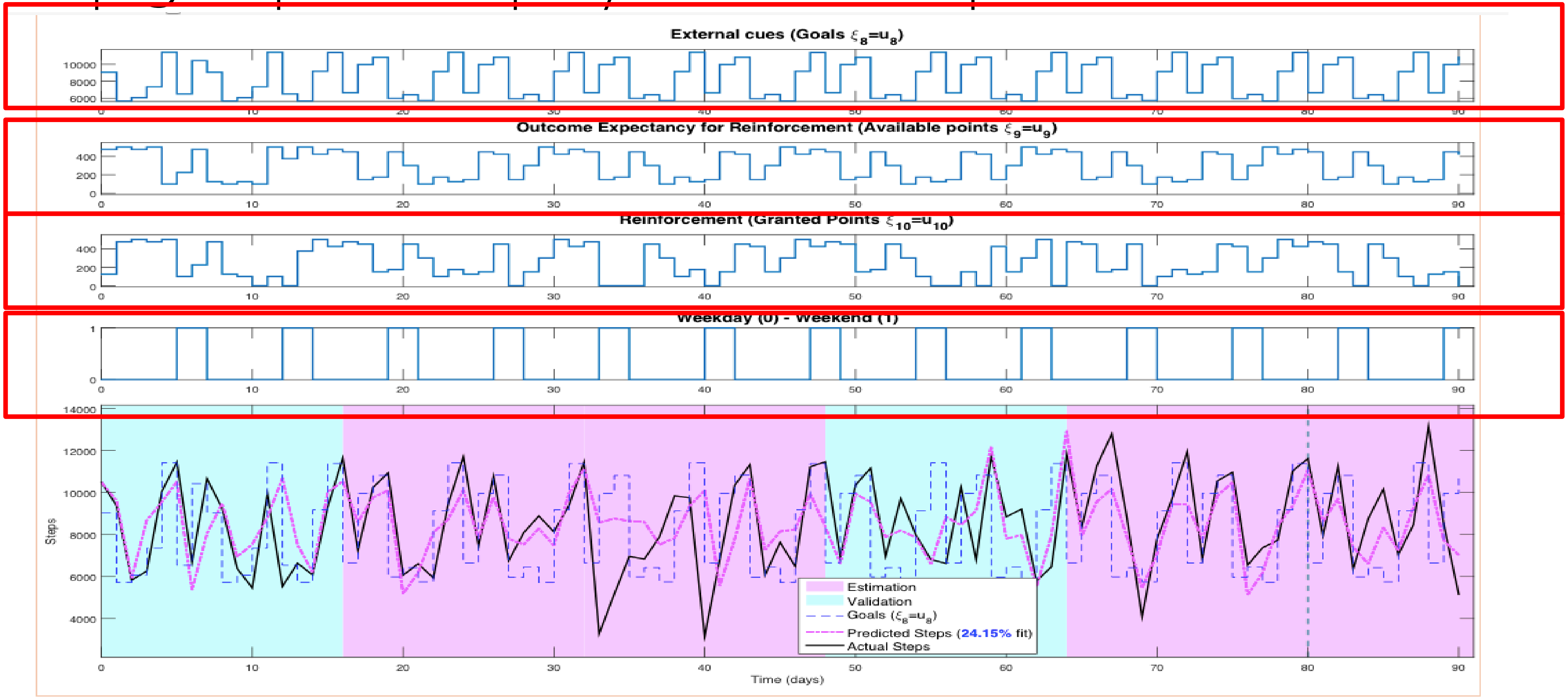


Figure 9 **Time-series plot of a fitted 4-input model that was selected one of the participants.**

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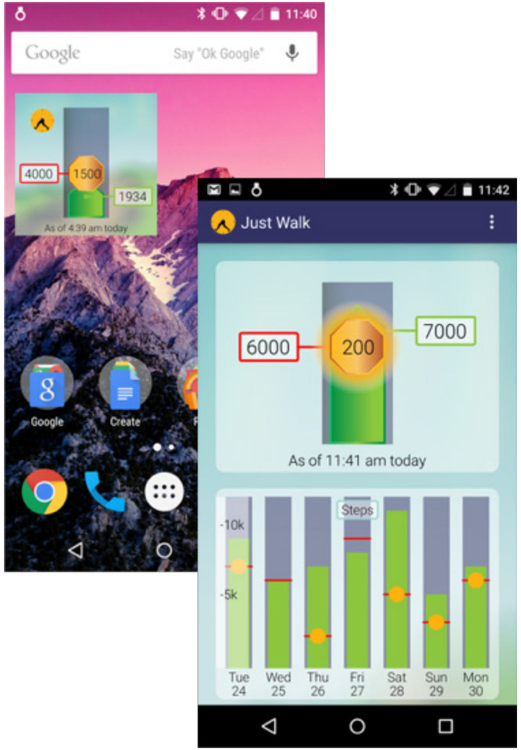
Korinek et al. *JBM, 2018;* Freighoun et al. 2017, *ACC;* Phatak et al. JBI, 2018;
Hekler et al. JMIR, 2018

Step 3 (cont). Study: "Just Walk"



Korinek et al. *JBM, 2018*; Freighoun et al. 2017, *ACC;* Phatak et al. JBI, 2018; Hekler et al. JMIR, 2018

Step 3 (cont) Participants

- BMI 33.7 ± 6.7
- 22 inactive, overweight Android users
- Age = 47 ± 6.2 years
- 87% women
- Living anywhere in the US
- Average Baseline Median Steps: 4972 steps/day (*SE* = 482)

Korinek et al. *JBM, 2018;* Freighoun et al. 2017, *ACC;* Phatak et al. JBI, 2018; Hekler et al. JMIR, 2018

Step 3 (cont): Feasibility results

+2,650 (t=8.25, p<0.01)Average step increase from baseline to intervention

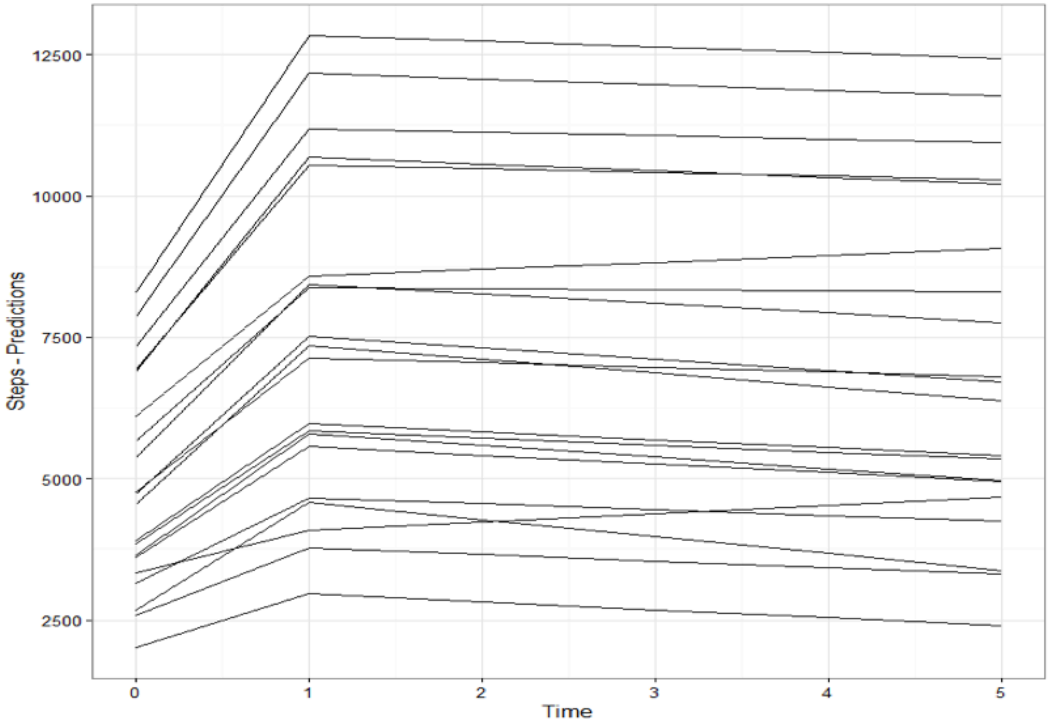
69% (*SD* = 24) Average goals met

>90% Adherence to EMA

100% enjoyed variable goals

85% found app easy to use

88% interested in continuing to use



Korinek et al. *JoBM*, 2018

Step 3 (cont). Data analysis

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

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

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

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

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

$y(k)$ 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 ($\|x\|_2 \stackrel{\text{def}}{=} \sqrt{x^T x}$).

Step 3 (cont). Dynamical modeling results

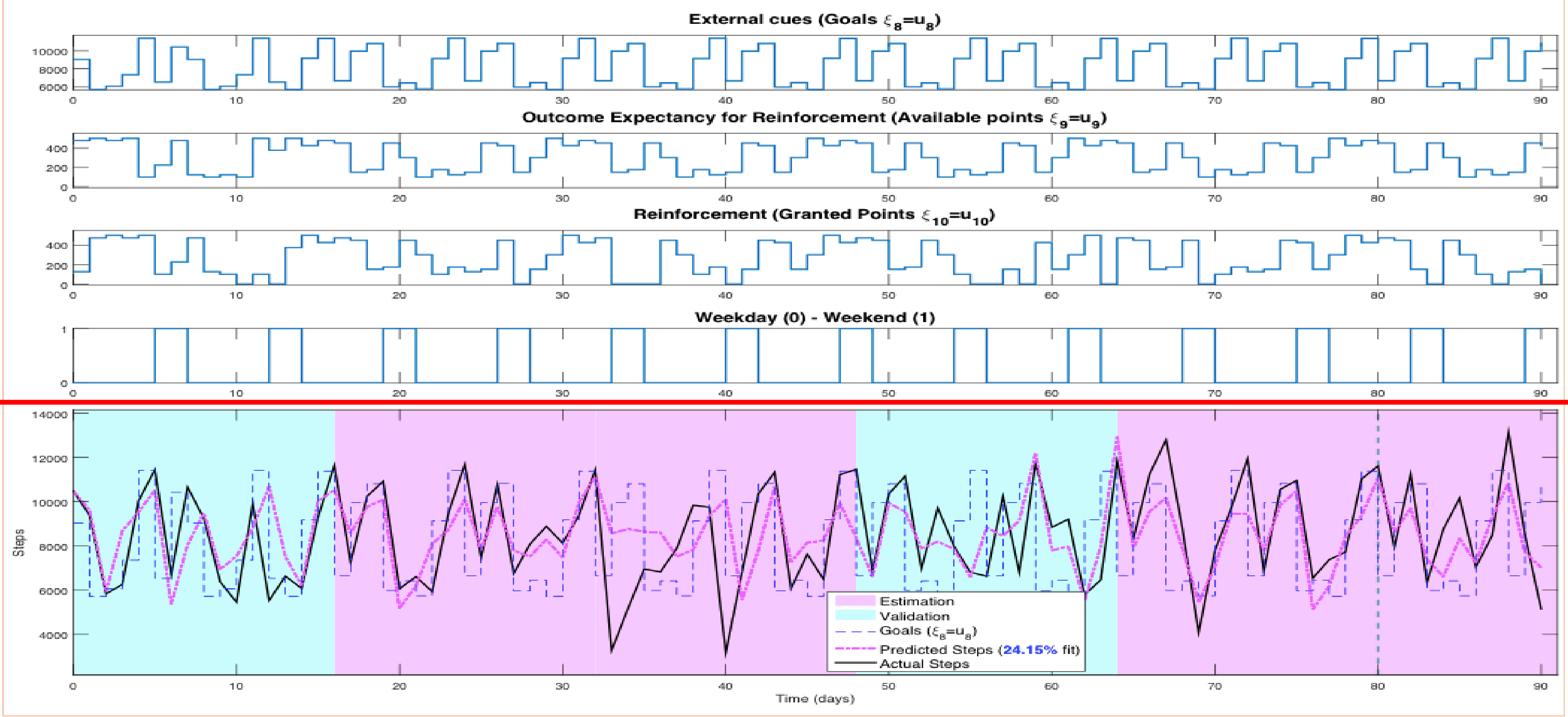


Figure 9 **Time-series plot of a fitted 4-input model that was selected one of the participants.**

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Phatak et al. JBI, 2018

What does this get us?

- A model to simulate future responses for each individual.
- This simulation enables dynamic, idiosyncratic, self-correcting decisions for each person.

C. A. Martín, D. E. Rivera and E. B. Hekler, (2*016)*
American Control Conference (ACC)

Individualized tailoring variables!

Table 6 Final Selected Models and Input Combinations

Model/Input Combination	Number of [illegible] for each [illegible] (n)
Weekend[b]	[illegible]
Typical & Weekend[b]	[illegible]
Busy[b]	2
Base Model[a]	1
Stress[b]	1
Typical[b]	1
Busy & Weekend[b]	1
Stress & Typi[illegible]	1
Busy & S[illegible]	1
Stre[illegible]d[b]	1
[illegible]cal & Weekend[b]	1
[illegible]ypical & Weekend[b]	1

[illegible] - base model that includes goals, expected points and granted points
b = base model + specified inputs.

Assuming individualized tailoring variables are better, prior evidence tailoring variables would have been inappropriate for 75% of our sample

Phatak et al. JBI, 2018

It's easier than you think…

- There's likely a control theory person at your school
- Standard toolkits in MatLab
  - Translatable to R

Normal intervention development steps

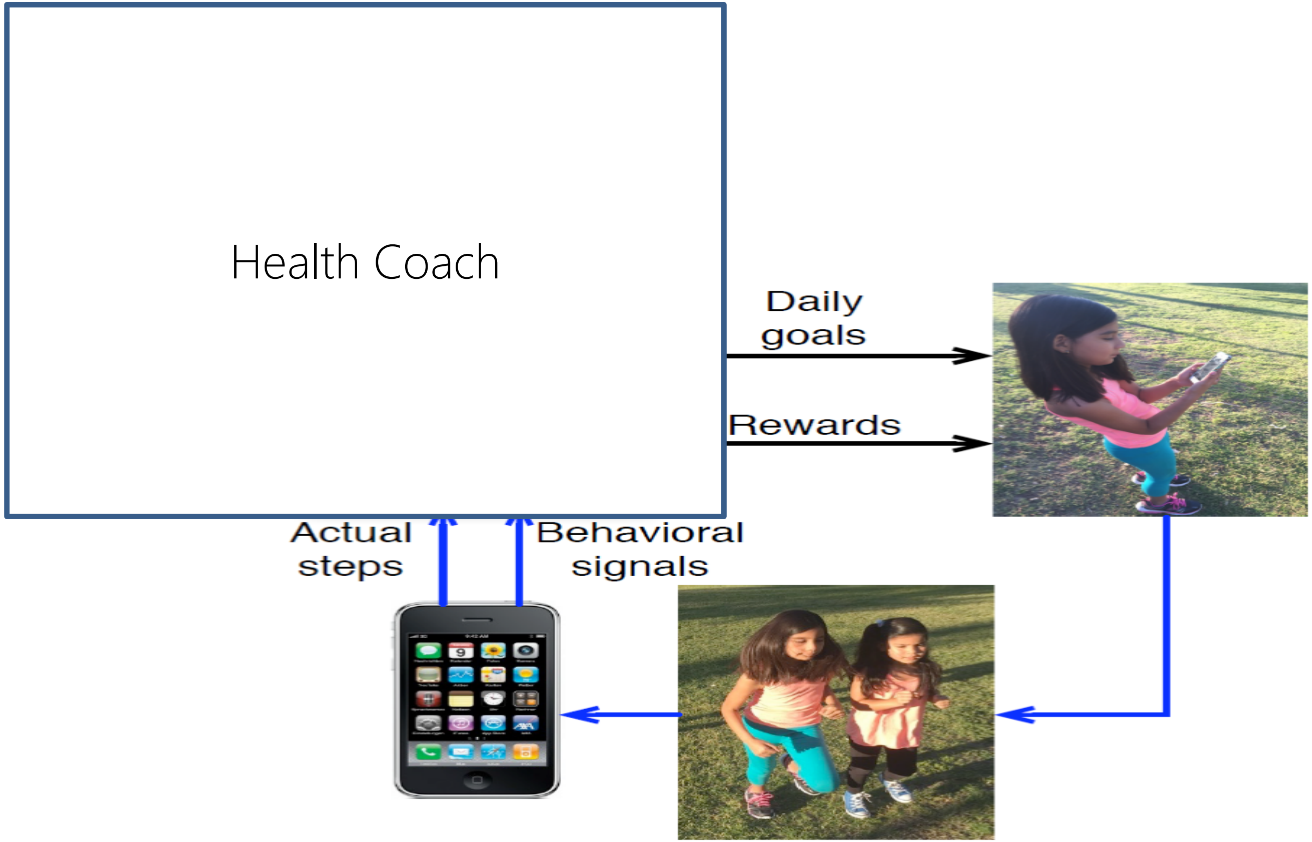
- Lit review - organize your understanding of prior work
- Define a hypothesis
- Test your hypothesis in naturalistic setting
  - e.g., observational trial/EMA trial
- Design your intervention
- Test your intervention

Step 4: Define optimization criteria & controller (design your intervention)

- Physical activity
  - Initiation "Set-point"
    - 10,000 steps/day, on average per week
    - +3,000 steps/day, on average per week relative to baseline
  - Transitions (both positive & lapses/relapses):
    - achieving 10,000 steps/day set point for 3 consecutive weeks OR
    - AFTER at least 6 months, +3,000 steps/day set point for 3 weeks.
  - Maintenance
    - Continue to meet PA targets
    - Reduce total interactions, ideally, to 0, except self-tracking

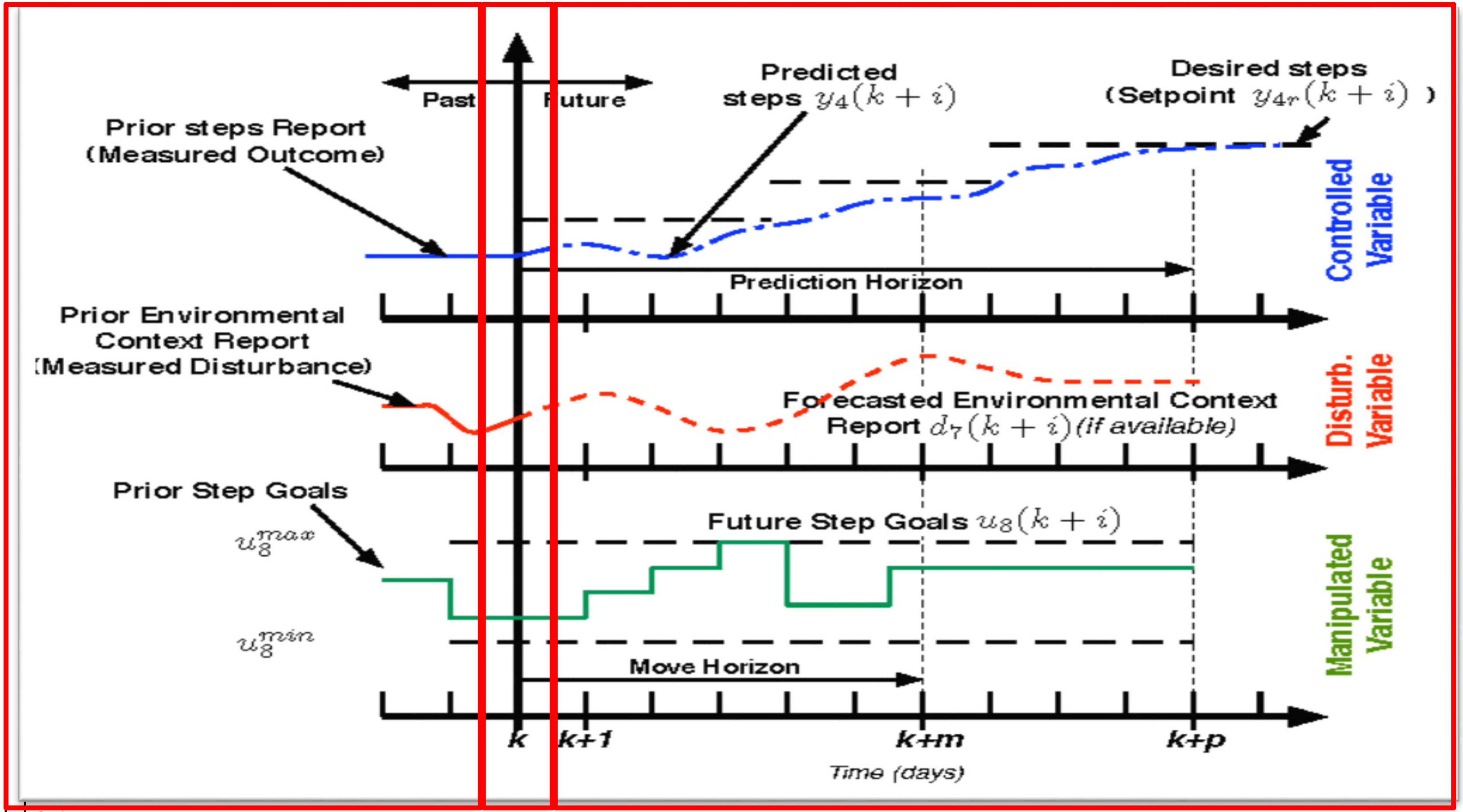
Hekler et al. *JMIR,* 2018

Closing the intervention loop



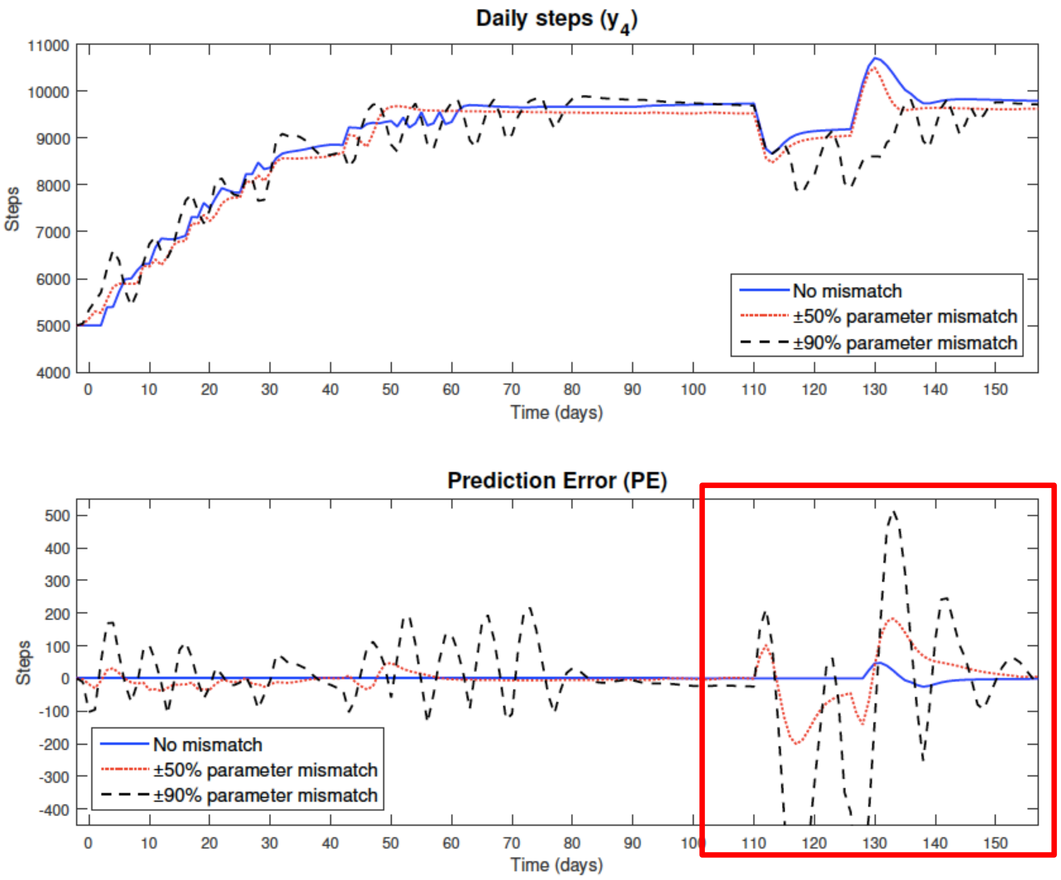
C. A. Martín, D. E. Rivera and E. B. Hekler, “A decision framework for an adaptive behavioral intervention for physical activity using hybrid model predictive control,” *2016 American Control Conference (ACC)*, Boston, MA, 2016, pp. 3576-3581.

Step 4. Design the controller



Martin, Rivera, & Hekler *Am. Control Conference (2015; 2016)*

Step 4 (optional): Examine robustness via simulation



Martin, Rivera, & Hekler (2016)

Normal intervention development steps

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- Design your intervention
- Test your intervention

Step 5: Conduct a Control Optimization Trial (COT) (test your intervention)

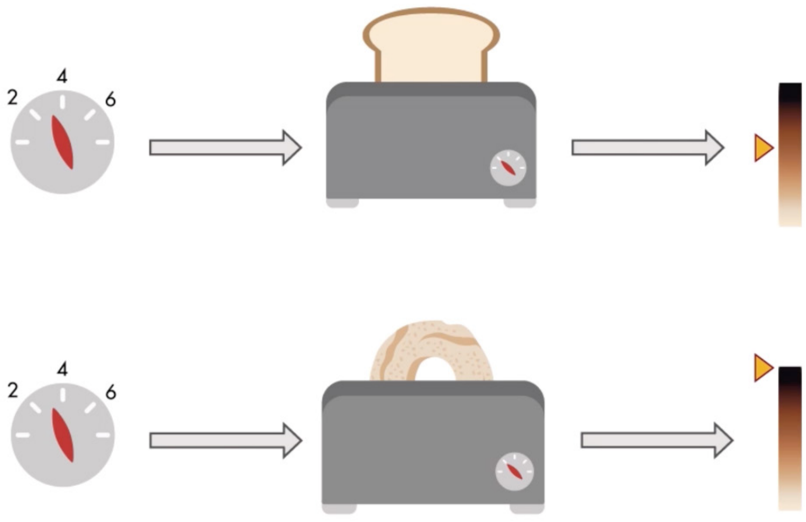
- Clearly specified adaptive intervention (already discussed)

- Design of sub-experiments and data analysis plan

- Conduct the trial and the analyses

COT sub-experiment options

- Open loop system ID

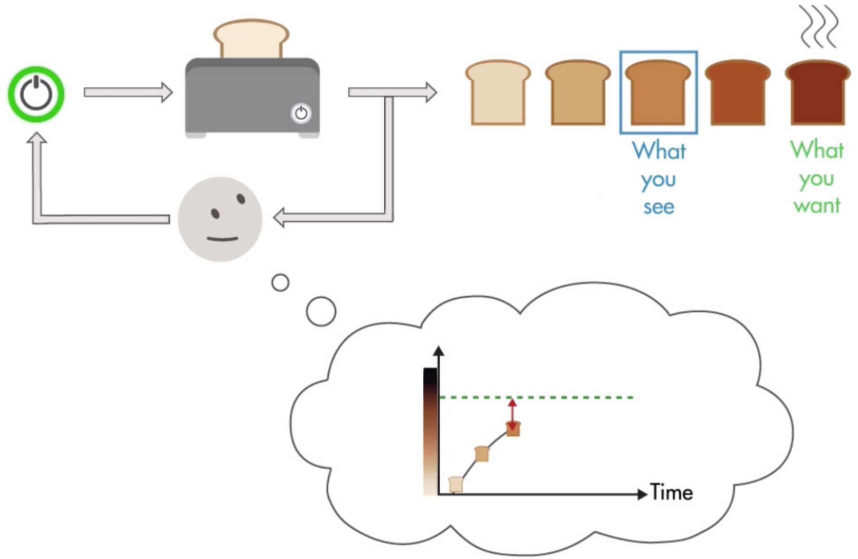


Tests understanding of the "system"

a) **theory-testing**

b) **individualized tailoring variable selection**

- Closed loop controller optimization



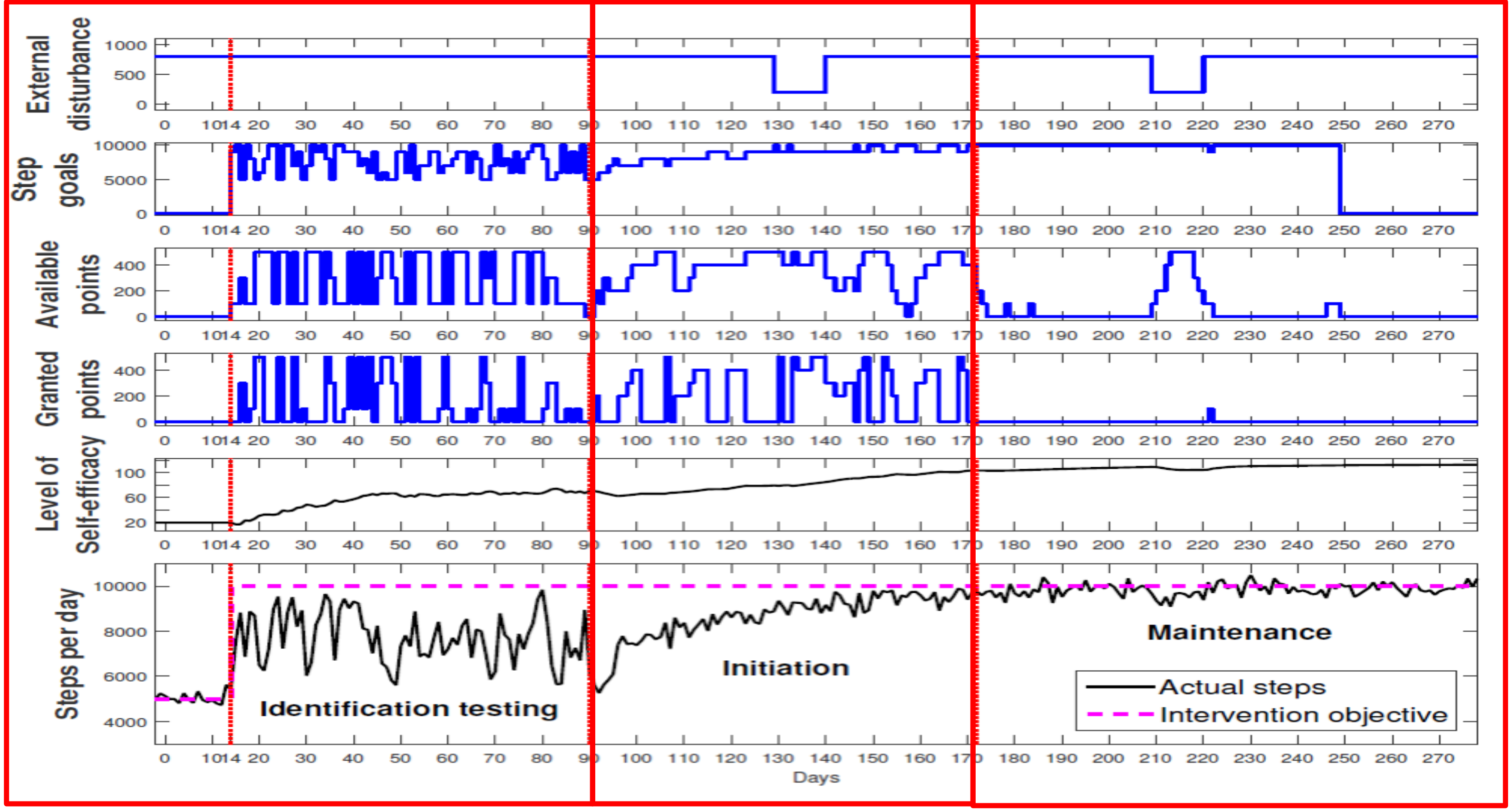
Tests understanding of the feedback/ decision rule

a) **real-time algorithm optimization**

@ehekler https://www.mathworks.com/videos/understanding-control-systems-part-1-open-loop-control-systems-123419.html

https://www.mathworks.com/videos/understanding-control-systems-part-2-feedback-control-systems-123501.html

Proposed COT example



Open-loop System ID

Closed loop optimization (initiation)

Closed loop optimization (maintenance)

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What does this get us ?

- Immediate benefits to individual
  - Individualized models
    - Enables simulations of future responses for each person
  - Individualized tailoring variables
    - Enables matching the intervention to each person
  - Real-time optimization algorithm
    - Enables perpetual adaptation to changing people and contexts
- Secondary optimization benefits
  - Rigorous data about each adaptive intervention element
    - Enables data-driven optimization of elements (e.g., tailoring variables, algorithms)
  - Effect size estimates of intervention components via stats
    - Enables estimation of generalized effect of intervention components
  - Rich experimental data
    - Enables dynamic theory testing in alignment with Riley, Rivera, et al's call (Riley et al 2011)

MOST & Control Systems Engineering

- MOST
- Preparation
  - Create a conceptual framework
  - Select intervention components/options
  - Conduct a feasibility study
  - Define optimization criteria
- Optimization
  - Run an optimization trial (e.g., FT, SMART, or MRT)
- Evaluation
  - RCT of "optimized" intervention package compared to meaningful comparator

- Control Engineering
- Step 1: Derive a dynamical model
- Step 2: Define intervention options and outcomes
- Step 3: Conduct a System Identification Experiment
- Step 4: Design the Controller, Including Optimization Criteria
- Step 5: Conduct a Control Optimization Trial (COT)
- Evaluation
  - RCT comparing COT intervention to meaningful comparator

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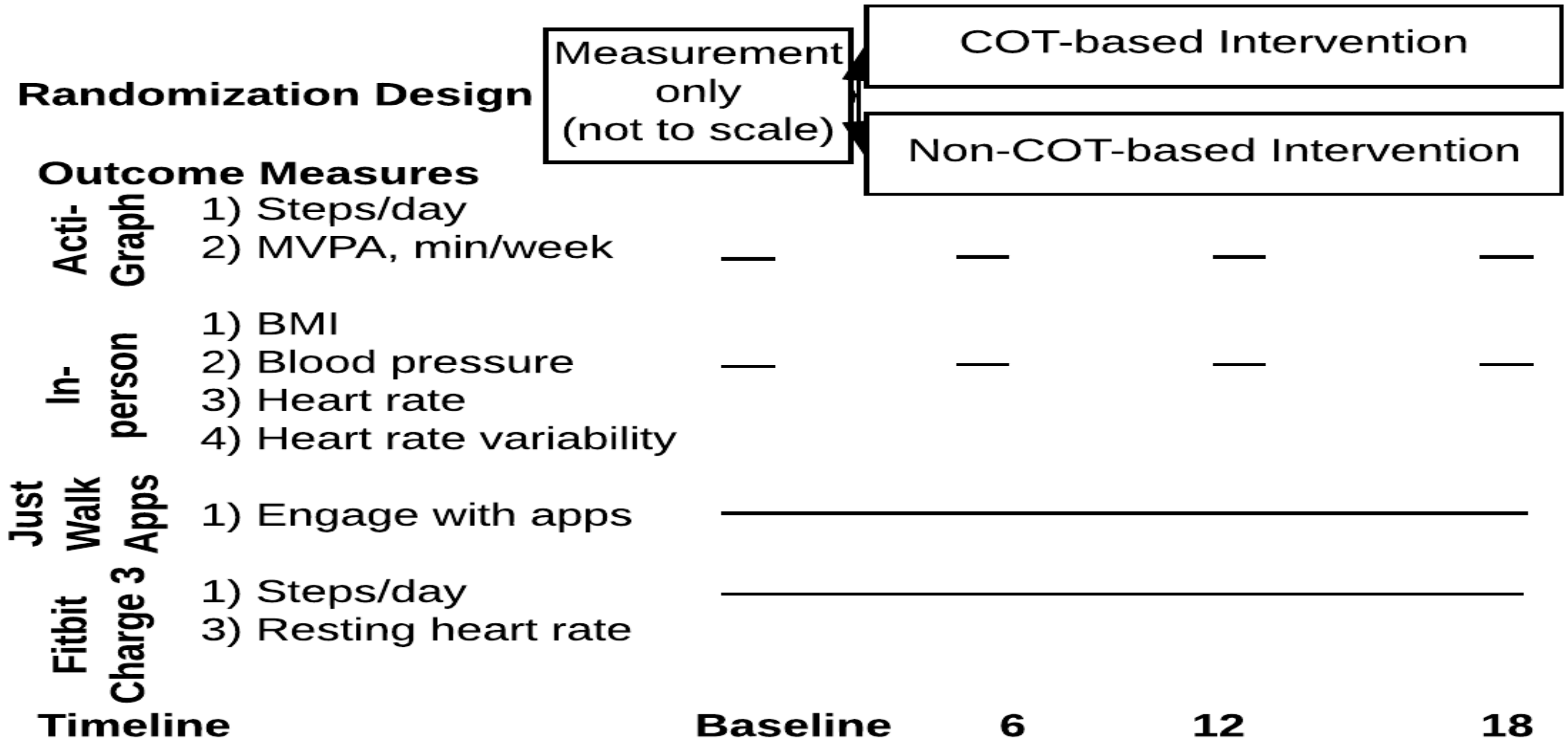
Rivera, Hekler et al. 2018; Hekler, Rivera, et al. *JMIR* 2018

Limitations

- COT approach has not been evaluated in an RCT
  - Prior work justifies advancing this approach
  - “Back to the future” as Carver, Sheier and others wanted to use these methods but technology was not ready
  - It now is

Testing a COT intervention in an RCT



Limitations

- COT approach has not been evaluated in an RCT
  - Prior work justifies advancing this approach
  - "Back to the future" as Carver and Sheier and others wanted to use these methods but technology not ready
  - It now is
- Just like stats, you need a control systems engineer
- Approach opens up ethical issues

Repertoire of optimization trials

- Intervention package
  - Factorial/fractional factorial trial (FT)
- Infrequent, key decision rules (e.g., clinical practice)
  - Sequential Multiple Assignment Randomized Trial (SMART)
- Bout-specific decision rules (i.e., just-in-time adaptive interventions; JITAIs)
  - Micro-randomization Trials (MRTs)
- Gradual, non-linear, idiosyncratic change
  - Control Optimization Trial (COT)

Take-home points

- If <u>reducing lapses/relapses</u> or <u>promoting maintenance/abstinence</u> is your goal, then a control optimization trial (COT) might help you.

- It’s not easy, but it’s easier than you think.

Helpful references

- Riley, W.T., C.A. Martin, D.E. Rivera, E.B. Hekler, M.A. Adams, M.P. Buman, M. Pavel and A.C. King, "Development of a dynamic computational model of social cognitive theory," *Translational Behavioral Medicine*, 6 (4), pp.483-495, (2016).
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