Improving Mobile Health Interventions

JOOLHEALTH

BariFit

Susan A Murphy
The Fields Institute
Toronto

MD2K
Center of Excellence for Mobile Sensor Data-to-Knowledge

The Methodology Center
advancing methods, improving health

Experiment to Continually Improve

- "Iterative nature of experimentation" (RA Fisher & G. Box)
- "At Google, experimentation is practically a mantra; we evaluate almost every change that potentially affects what our users' experience." (4 Google scientists)
- "Online experiments are widely used to compare specific design alternatives, but they can also be used to produce generalizable knowledge and inform strategic decision making. Doing so often requires sophisticated experimental designs, iterative refinement, and careful logging and analysis." (3 Facebook scientists)

Smart wt loss

JOOLHEALTH

HeartSteps

BariFit

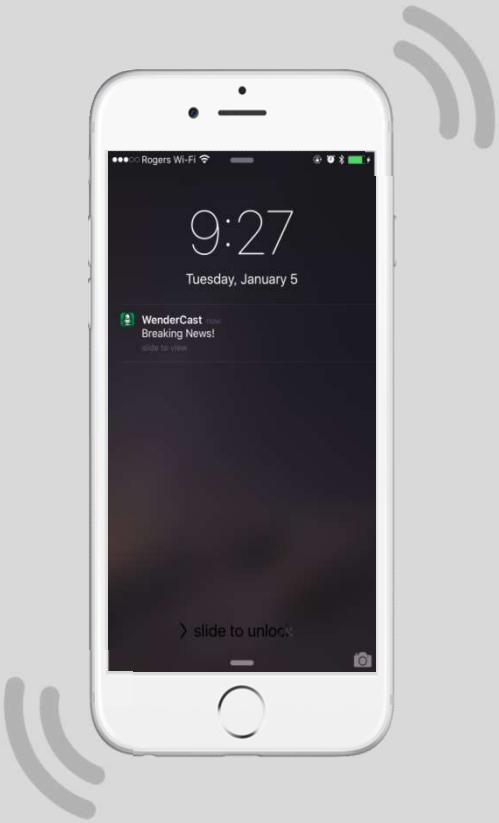
SARA

Sense^{2}STOP

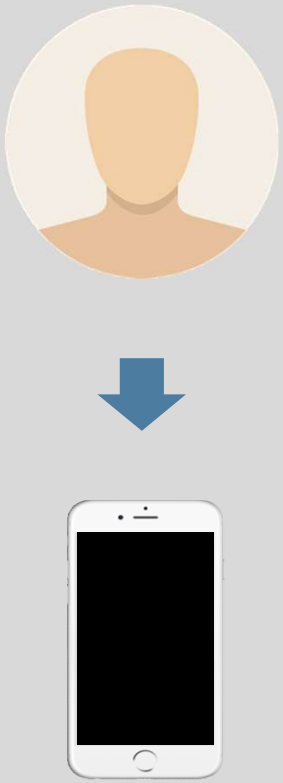
https://methodology.psu.edu/ra/adap-inter/mrt-projects#proj

Mobile Intervention Treatments

PUSH

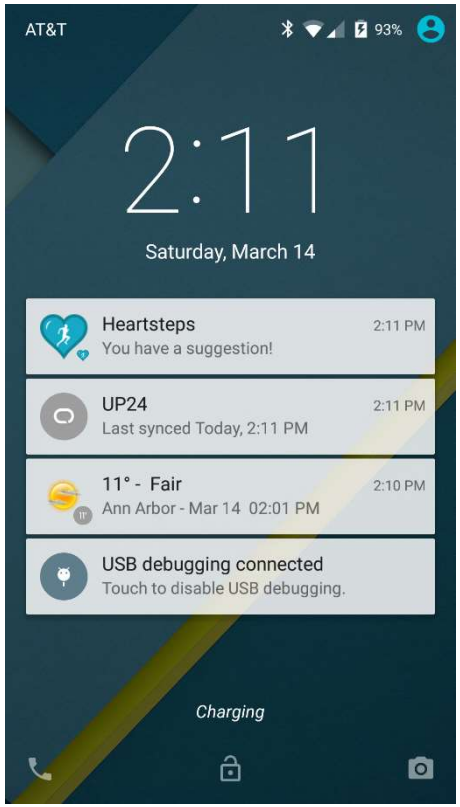


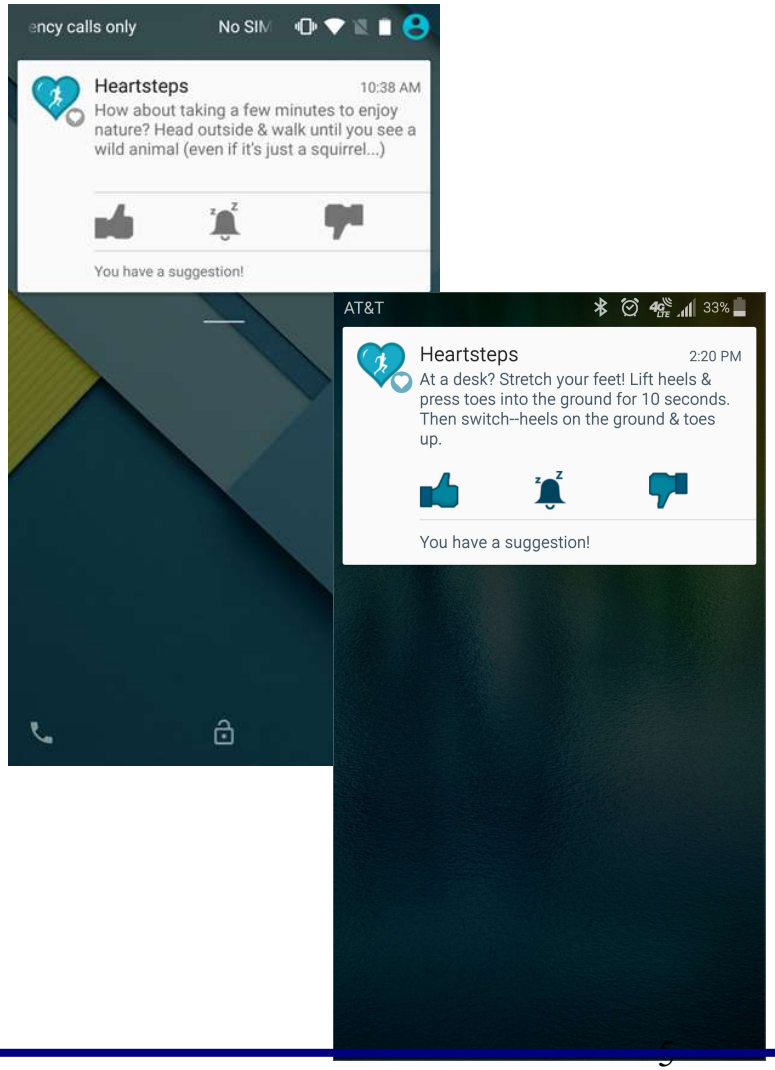
PULL



Example Pushes

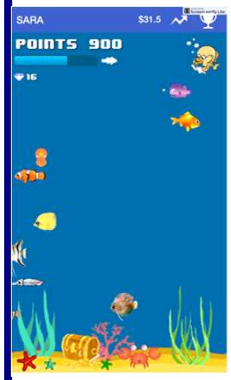
In-the-Moment Tailored Activity Suggestions





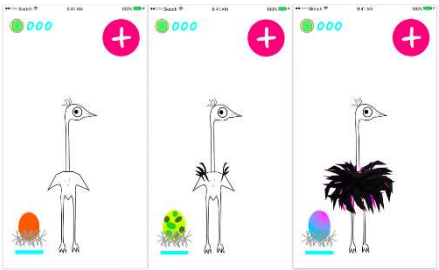
SARA
Substance
Abuse
Research
Assistant

Optimizing mHealth Engagement



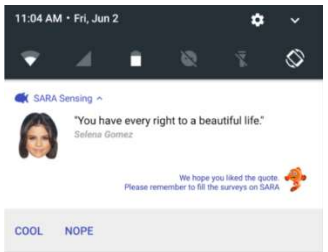
Pull: When you open the app, should the interface provide engagement rewards via a growing aquarium?

- Should the suggested user interface differ by baseline user characteristics?



Push: Should the app notify the user to provide an inspirational message?

- Should these messages appear when the user is more or less engaged?



HeartSteps (PI Klasnja)

Goal: Develop an mobile activity coach for individuals who are high risk of heart disease

Three iterative studies:

- 42 day micro-randomized pilot study with sedentary individuals,
- 90 day micro-randomized study,
- 365 day personalized study

HeartSteps V1

Context provided via data from:

Wearable band → activity and sleep quality;

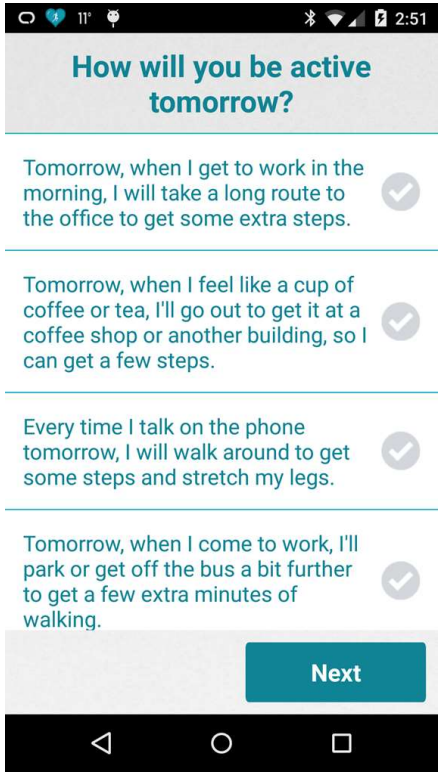
Smartphone sensors → busyness of calendar, location, weather;

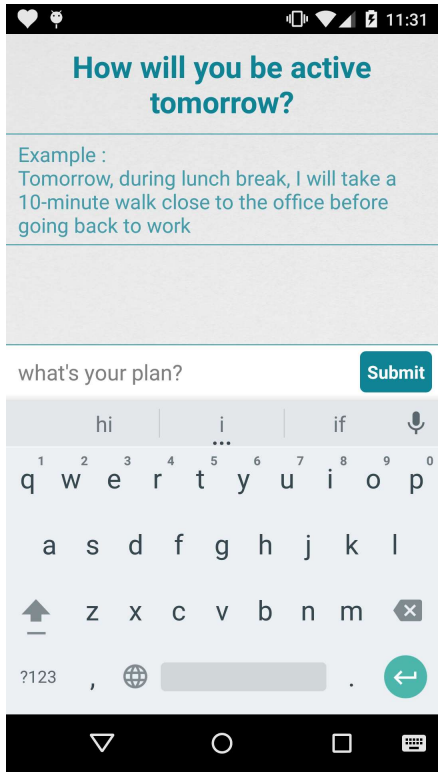
Self-report → stress, user burden

How might the smartphone help you plan your activity tomorrow?

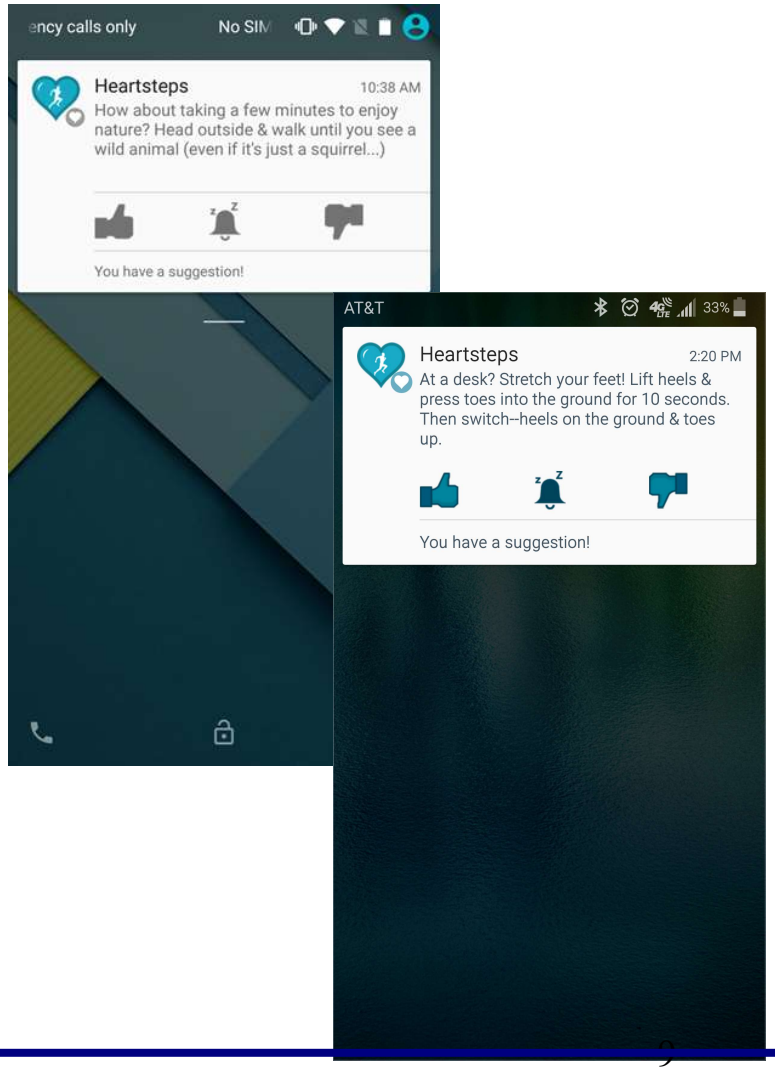
In which contexts should the smartphone provide you with a tailored activity suggestion?

Evening Planning





In-the-Moment Tailored Activity Suggestion



Structure of a mobile health intervention that uses wearable devices to sense the context and "push" treatments

Structure of Mobile Health Intervention

1) Decision Points: times, *t*, at which a treatment might be delivered or "pushed"
   1) Regular intervals in time (e.g. every 10 minutes)
   2) At user demand

<u>HeartSteps</u>: approximately every 2-2.5 hours: pre-morning commute, mid-day, mid-afternoon, evening commute, after dinner

Structure of Mobile Health Intervention

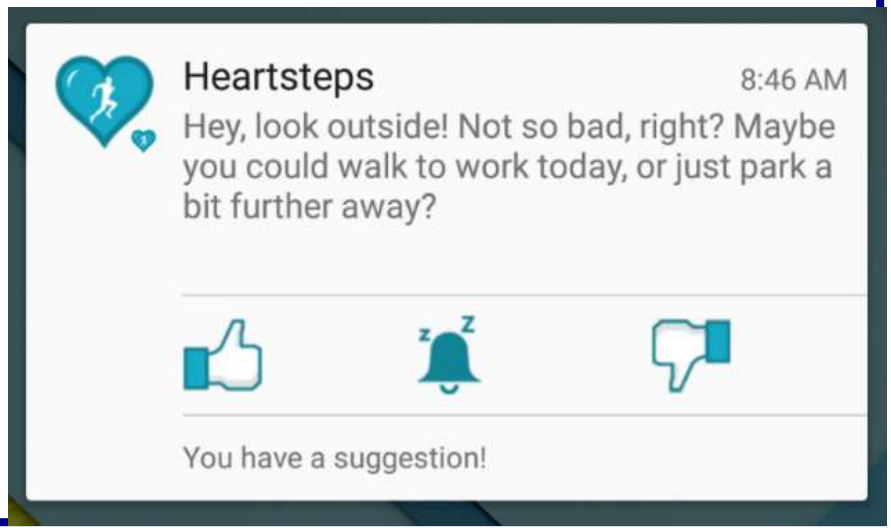
2) Observations at decision point *t*
   1) Passively collected (via sensors)
   2) Actively collected (via self-report)

<u>HeartSteps</u>: classifications of activity, location, weather, step count, busyness of calendar, usefulness ratings, adherence…….

Structure of Mobile Health Intervention

3) Intervention Options A_t
   1) Types of treatments/engagement strategies that can be provided at a decision point, t
   2) Whether to provide a treatment

<u>HeartSteps</u>: tailored activity suggestion (yes/no)



Availability

Activity suggestions can only be delivered if the individual is currently *available*. -- I_t=1 if available, I_t=0 if not

- Unavailability is not the same as nonadherence!

<u>HeartSteps</u>: Unavailable if sensors indicate that the individual may be operating a vehicle, is walking or has turned off the intervention.

Structure of Mobile Health Intervention

4) Proximal Outcome Y_{t+1}

<u>HeartSteps</u>: Step count over 30 minutes following decision point, t

Treatment Effects

The tailored activity suggestions are designed to be near-term actionable.

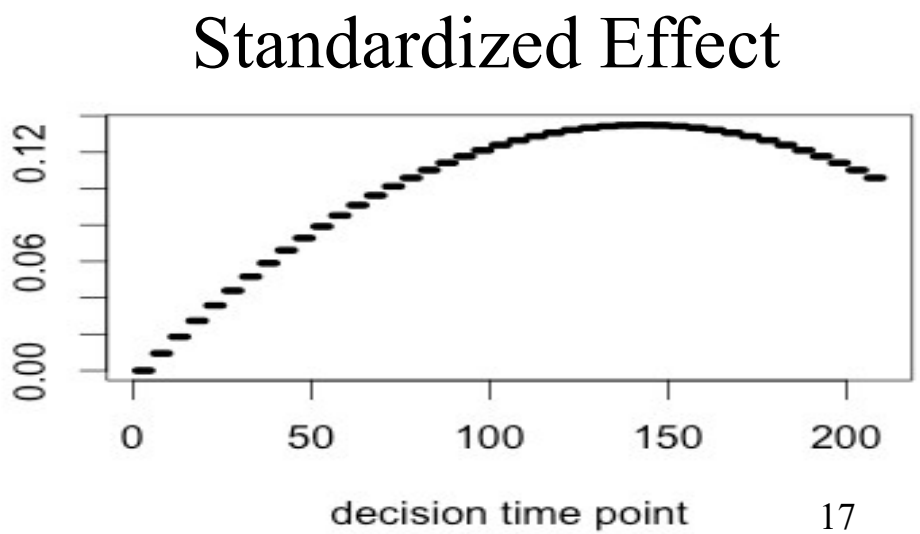
Does the tailored activity suggestion influence step count in the subsequent 30 minutes?

- Does this effect deteriorate over time?

Treatment Effect

Effect of activity suggestion on step count is likely time-varying

What does this effect mean?



HeartSteps
Micro-Randomized Trial

On each participant, randomize delivery of a mobile intervention component (activity suggestion) each time that component *may be* delivered.

Activity suggestion (210 randomizations)

- If available, provide an activity suggestion with probability .6; do nothing with probability .4

Data analyses following the micro-randomized mobile health trial

Conceptual Models

Generally data analysts fit a series of increasingly more complex models:

$$Y_{t+1} \text{ “}\sim\text{” } \alpha_0 + \alpha_1^T Z_t + \beta_0 A_t$$

and then next,

$$Y_{t+1} \text{ “}\sim\text{” } \alpha_0 + \alpha_1^T Z_t + \beta_0 A_t + \beta_1 A_t S_t$$

and so on…

- Y_{t+1} is subsequent activity over next 30 min.
- $A_t = 1$ if activity suggestion and 0 otherwise
- Z_t summaries formed from t and past/present observations
- S_t potential moderator (e.g., current weather is good or not)

Conceptual Models

Generally data analysts fit a series of increasingly more complex models:

$$Y_{t+1} \text{ “}\sim\text{” } \alpha_0 + \alpha_1^T Z_t + \beta_0 A_t$$

and then next,

$$Y_{t+1} \text{ “}\sim\text{” } \alpha_0 + \alpha_1^T Z_t + \beta_0 A_t + \beta_1 A_t S_t$$

and so on…

$\alpha_0 + \alpha_1^T Z_t$ is used to reduce the noise variance in Y_{t+1} (Z_t is sometimes called a vector of control variables)

Causal Effects

$$Y_{t+1} \text{ “}\sim\text{” } \alpha_0 + \alpha_1^T Z_t + \beta_0 A_t$$

β_0 is the effect, marginal over all observed and all unobserved variables, of the activity suggestion on subsequent activity

$$Y_{t+1} \text{ “}\sim\text{” } \alpha_0 + \alpha_1^T Z_t + \beta_0 A_t + \beta_1 A_t S_t$$

$\beta_0 + \beta_1$ is the effect when the weather is good (S_t=1), marginal over other observed and all unobserved variables, of the activity suggestion on subsequent activity.

Goal

- Develop data analytic methods that are consistent with our scientific understanding of the meaning of the β coefficients

- Challenges:
  - Time-varying treatment (A_t, $t=1,\ldots T$)
  - "Independent" variables: Z_t, S_t, I_t that may be affected by prior treatment
- Robustly facilitate noise reduction via use of controls, Z_t

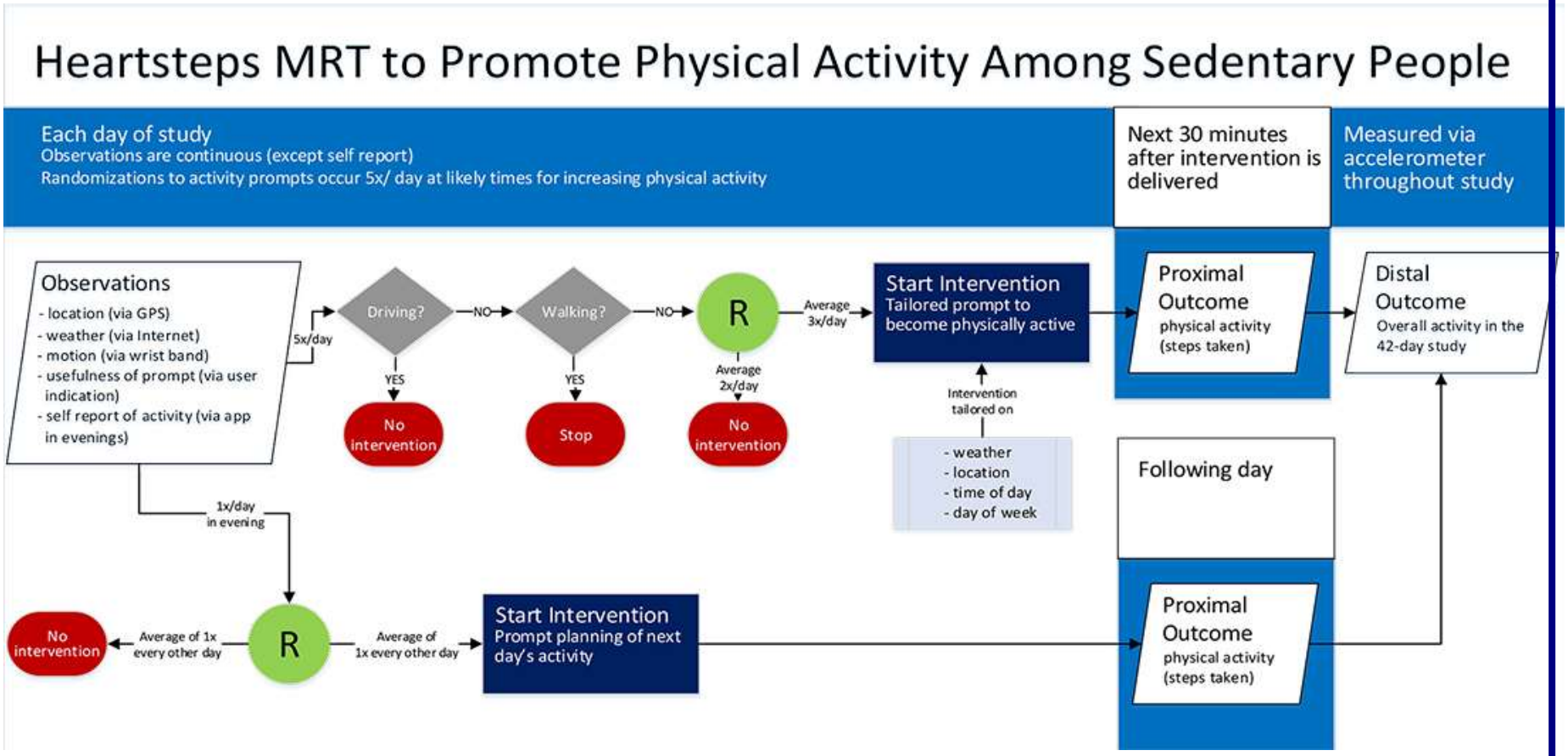
"Centered and Weighted Least Squares Estimation"

- Simple method for complex data!
- Enables unbiased inference for a causal, marginal, treatment effect (the β's)
- Inference for treatment effect is not biased by how we use the controls to reduce the noise variance in Y_{t+1}

JASA, 2018

Application of the “Centered and Weighted Least Squares Estimation” method in an initial analysis of HeartSteps

HeartSteps V1



PI: P Klasnja
Location: University of Michigan
Funding: NHLBI/NIA R01HL125440

On each of $n=37$ participants:

a) Activity suggestion, A_t

- **Provide a suggestion with probability .6**
  - a tailored sedentary-reducing activity suggestion (probability=.3)
  - a tailored walking activity suggestion (probability=.3)
- **Do nothing (probability=.4)**

- 5 times per day * 42 days= 210 decision points

Conceptual Models

$$Y_{t+1} \text{ “}\sim\text{” } \alpha_0 + \alpha_1 Z_t + \beta_0 A_t$$

$$Y_{t+1} \text{ “}\sim\text{” } \alpha_0 + \alpha_1 Z_t + \alpha_2 d_t + \beta_0 A_t + \beta_1 A_t d_t$$

- $t=1,\ldots T=210$
- Y_{t+1} = log-transformed step count in the 30 minutes *after* the tth decision point,
- $A_t = 1$ if an activity suggestion is delivered at the tth decision point; $A_t = 0$, otherwise,
- Z_t = log-transformed step count in the 30 minutes *before* the tth decision point,
- d_t =days in study; takes values in (0,1,….,41)

HeartSteps Analysis

$$Y_{t+1} \text{ “}\sim\text{” } \alpha_0 + \alpha_1 Z_t + \beta_0 A_t \text{, and}$$

$$Y_{t+1} \text{ “}\sim\text{” } \alpha_0 + \alpha_1 Z_t + \alpha_2 d_t + \beta_0 A_t + \beta_1 A_t d_t$$

Causal Effect Term	**Estimate**	**95% CI**	**p-value**
$\beta_0 A_t$ *(effect of an activity suggestion)*	$\hat{\beta}_0$=.13	(-0.01, 0.27)	.06
$\beta_0 A_t + \beta_1 A_t d_t$ *(time trend in effect of an activity suggestion)*	$\hat{\beta}_0$ = .51	(.20, .81)	<.01
	$\hat{\beta}_1$ = -.02	(-.03, -.01)	<.01

On each of *n=37* participants:

a) Activity suggestion

- Provide a suggestion with probability .6
  - **a tailored walking activity suggestion (probability=.3**)
  - **a tailored sedentary-reducing activity suggestion (probability=.3)**
- **Do nothing (probability=.4)**

- 5 times per day * 42 days= 210 decision points

HeartSteps Analysis

$$Y_{t+1} \text{ “}\sim\text{” } \alpha_0 + \alpha_1 Z_t + \beta_0 A_{1t} + \beta_1 A_{2t}$$

- $A_{1t} = 1$ if walking activity suggestion is delivered at the tth decision point; $A_{1t} = 0$, otherwise,
- $A_{2t} = 1$ if sedentary-reducing activity suggestion is delivered at the tth decision point; $A_{2t} = 0$, otherwise,

Causal Effect	Estimate	95% CI	p-value
$\beta_0 A_{1t} + \beta_1 A_{2t}$	$\hat{\beta}_0 = .21$ $\hat{\beta}_1 > 0$	(.04, .39) ns	.02 ns

Initial Conclusions

- The data indicates that there is a causal effect of the activity suggestion on step count in the succeeding 30 minutes.
  - This effect is primarily due to the walking activity suggestions.
  - This effect deteriorates with time
  - The walking activity suggestion initially increases step count over succeeding 30 minutes by approximately 271 steps but by day 20 this increase is only approximately 65 steps.

On each of *n=37* participants:

b) Evening planning prompt

- Provide a prompt with probability .5
  - **Prompt using unstructured activity planning for following day with probability=.25**
  - **Prompt using structured activity planning for following day with probability=.25**
- **Do nothing with probability=.5**

- 1 time per day * 42 days= 42 decision points

Initial Conclusions

- The data indicates that there is a causal effect of planning the next day's activity on the following day's step count
  - This effect is due to the unstructured planning prompts.
  - This effect occurs primarily on weekdays
  - On weekdays the effect of an unstructured planning prompt is to increase step count on the following day by approximately 780 steps.

Discussion

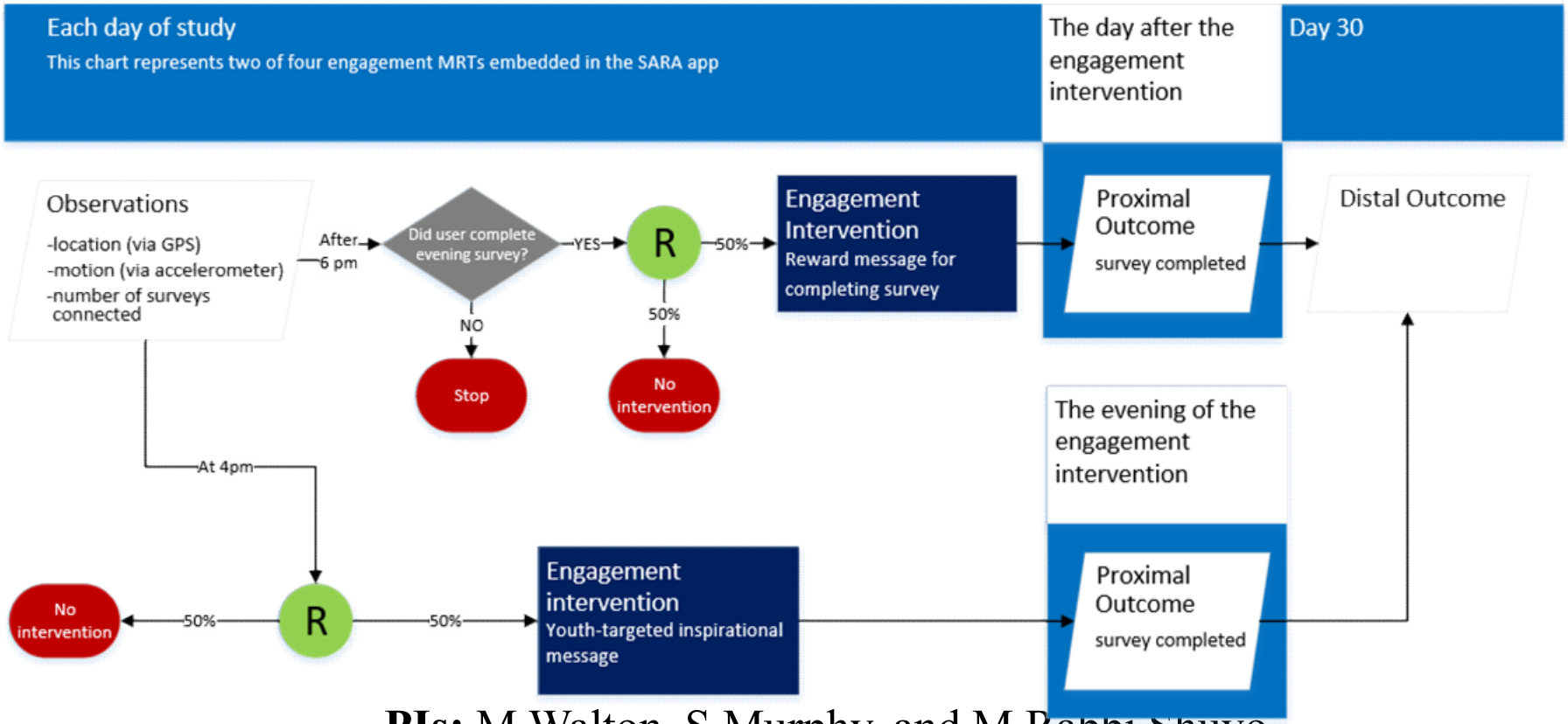
Problematic Analyses

- GLM & GEE analyses
- Random effects models & analyses
- Machine Learning Generalizations:
  - Partially linear, single index models & analysis
  - Varying coefficient models & analysis

--These analyses were not developed to take advantage of the micro-randomization. Can accidentally eliminate the advantages of randomization for estimating causal effects--

SARA

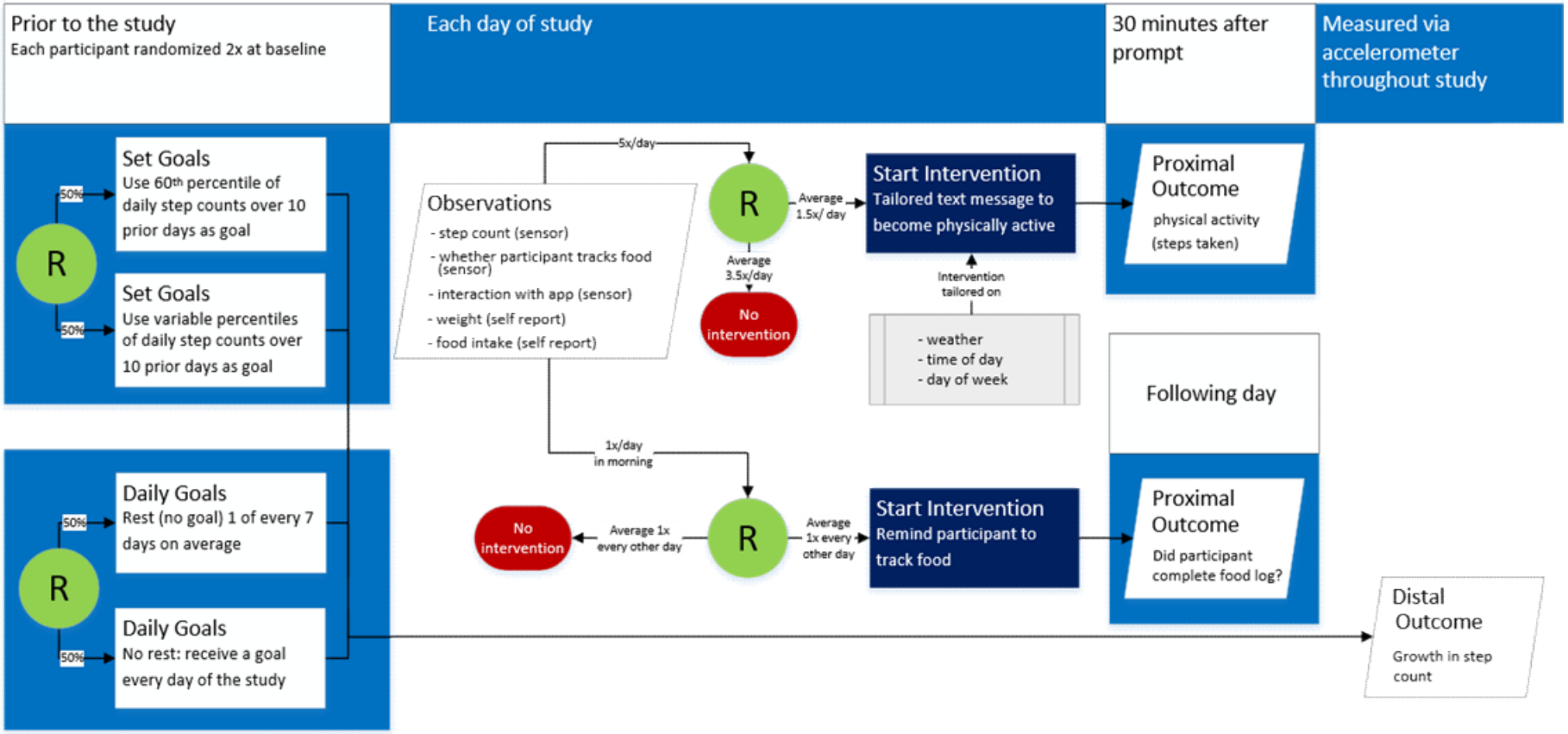
Data Collection MRT to Promote Engagement in Substance Use Research



PIs: M Walton, S Murphy, and M Rabbi Shuvo
Location: University of Michigan
Funding: Michigan Institute for Data Science (PI S. Murphy), University of Michigan Injury Center (PI M. Walton)

BariFit

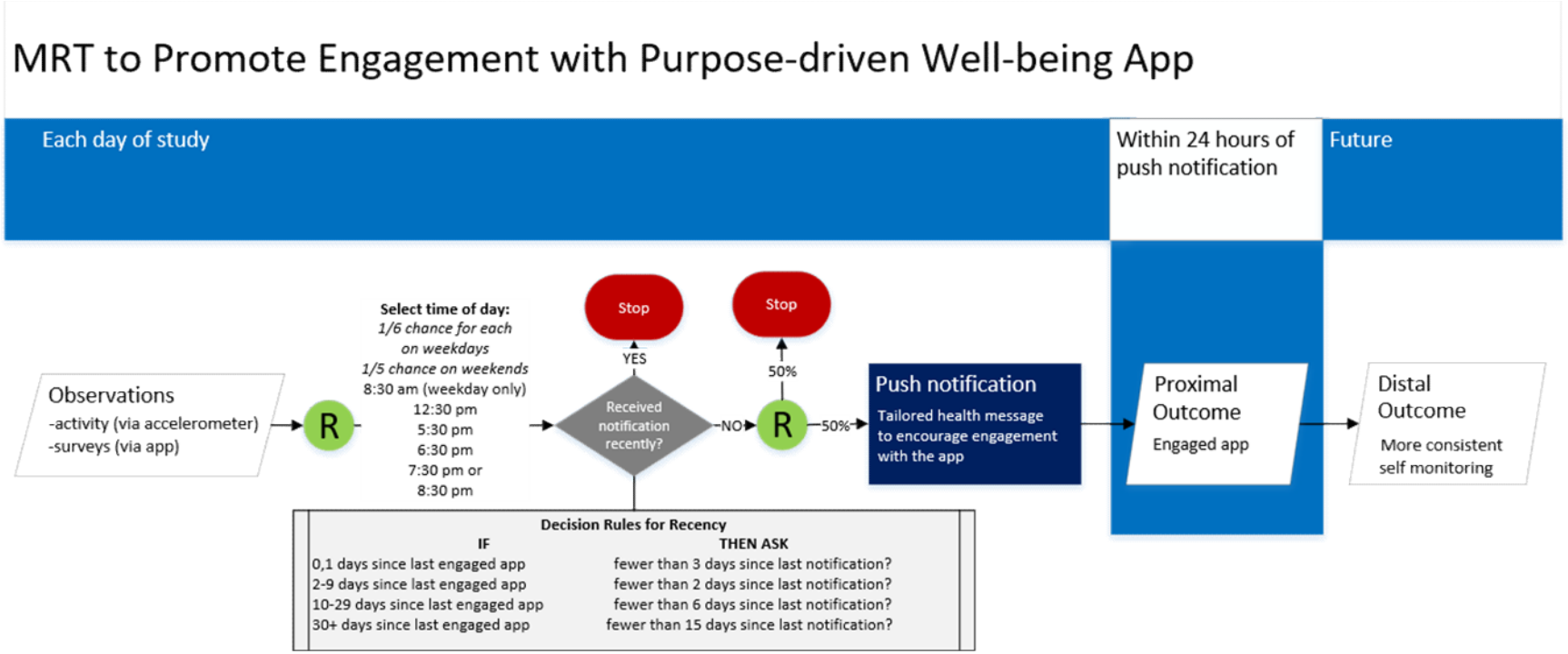
BariFit MRT to Promote Weight Maintenance Among People Who Received Bariatric Surgery



PI: P Klasnja

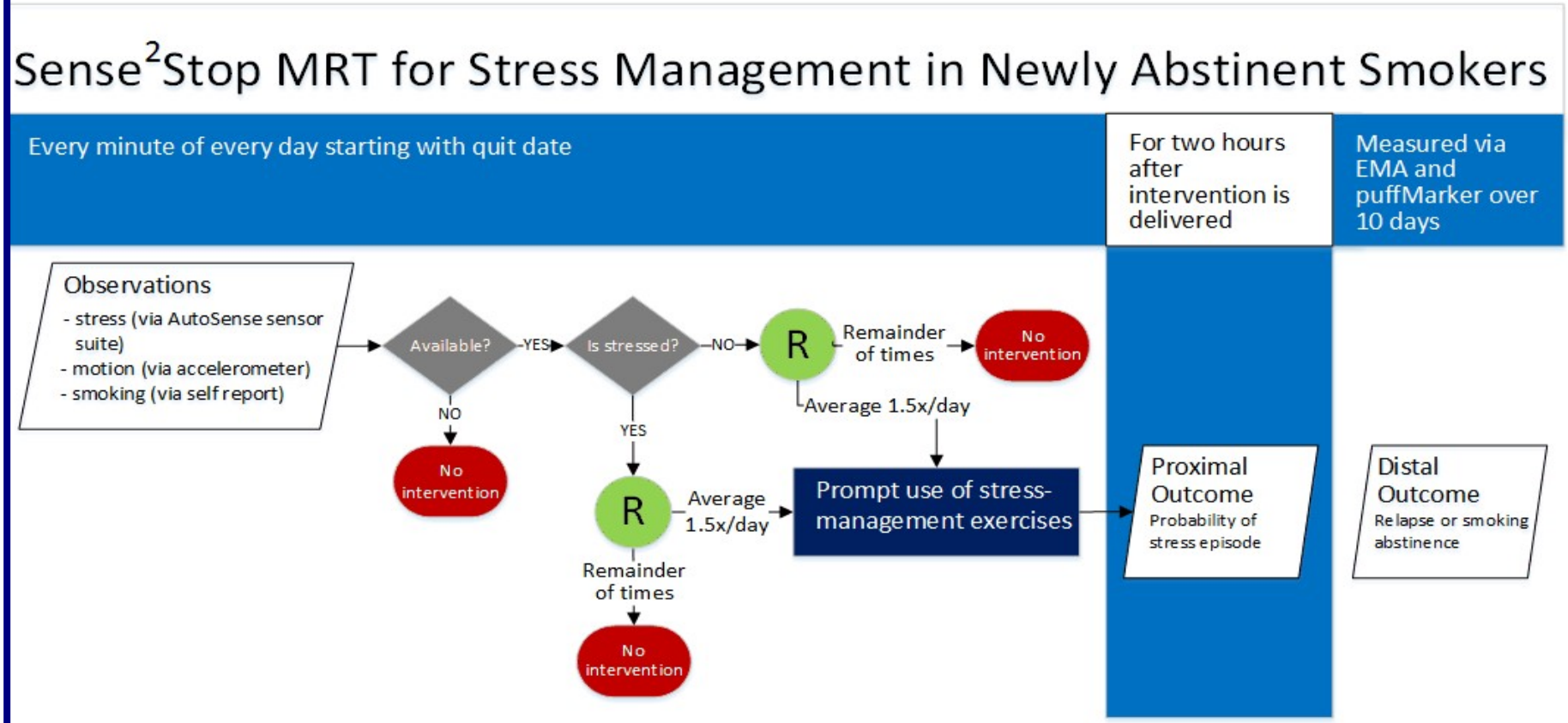
Location & Funding: Kaiser Permanente

Engagement with JOOL



PI: Victor Strecher, PhD, MPH, CEO of JOOL Health
Location & Funding: Ann Arbor, MI
URL: https://www.joolhealth.com

Sense^{2}Stop



PI: S Kumar

Location: Northwestern University, B. Spring, (P.I.)

Funding: NIBIB through funds provided by the trans-NIH Big Data to Knowledge initiative U54EB020404

Collaborators!