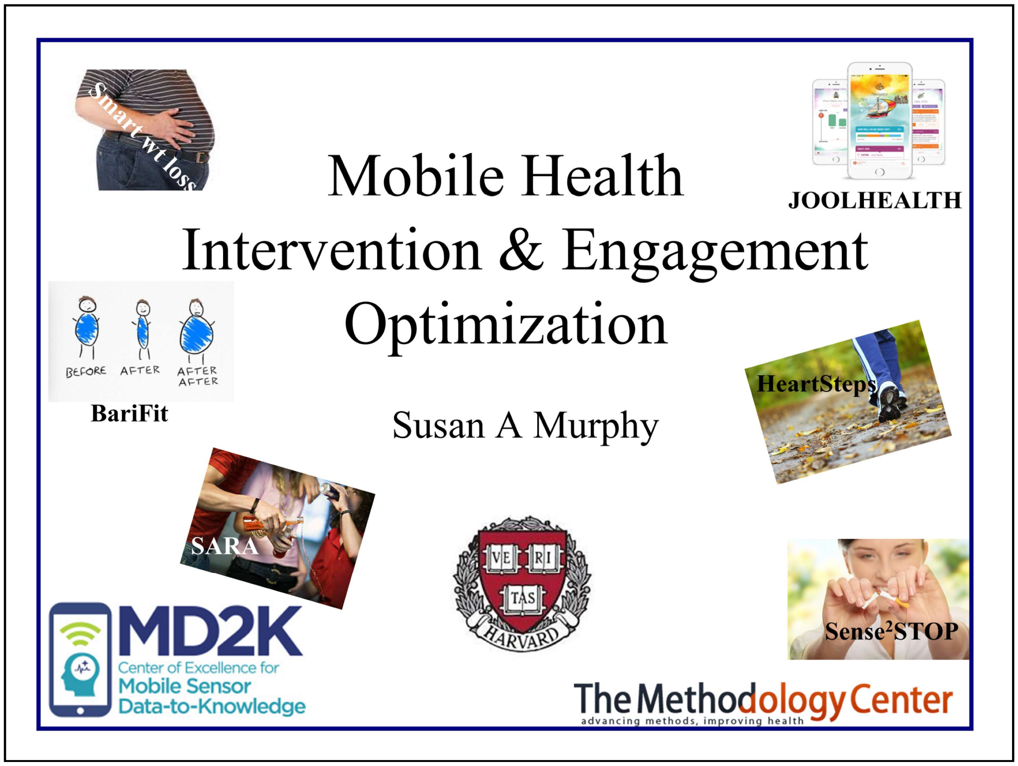

Title: Mobile Health Intervention and Engagement Optimization

Abstract: Mobile devices along with wearable sensors facilitate our ability to deliver supportive behavioral treatments to users anytime and anywhere. These treatments can include a wide variety of content such cognitive, behavioral, social and motivational support. These interventions are being developed and employed across a variety of health fields, including to improve medication adherence, encourage physical activity and healthier eating as well as to support recovery in addictions. Critical questions in the optimization of mobile health interventions include: "Does the user benefit from a particular type of mobile health notification or text message?" and "Does the user's current context such as location, time, mood impact the usefulness of the mobile health notification. In this talk we discuss the micro-randomized trial design and associated data analyses for use in optimizing mobile health interventions. We illustrate the ideas with the micro-randomized trials across a variety of fields.

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)

2

Fisher and G. Box in industrial engineering philosophy: “iterative nature of experimentation” when the underlying system is not under control. Always be clear is about what the goal is –what is it you want to optimize.

Data + idea -> deduction (used to test a theory)

Data – idea → induction (used to generate new theory)

Can change the objective after you experiment

http://www.statisticsviews.com/details/video/5018561/The-Iterative-Nature-of-Experimentation---Part-II-by-George-E_P_-Box.html

Quote from paper by 4 Google scientists: At Google, experimentation is practically a mantra; we evaluate almost every change that potentially affects what our users experience. Such changes include not only obvious user-visible changes such as modifications to a user interface, but also more subtle changes such as different machine learning algorithms that might affect ranking or content selection. Our insatiable appetite for experimentation has led us to tackle the problems of how to run more experiments, how to run experiments that produce better decisions, and how to run them faster.

Overlapping Experiment Infrastructure: More, Better, Faster Experimentation Diane Tang, Ashish Agarwal, Deirdre O’Brien, Mike Meyer Google, Inc. Mountain View,

CA [diane,agarwal,deirdre,mmm]@google.com

Quote from paper by 3 facebook scientists and cs at stanford: “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

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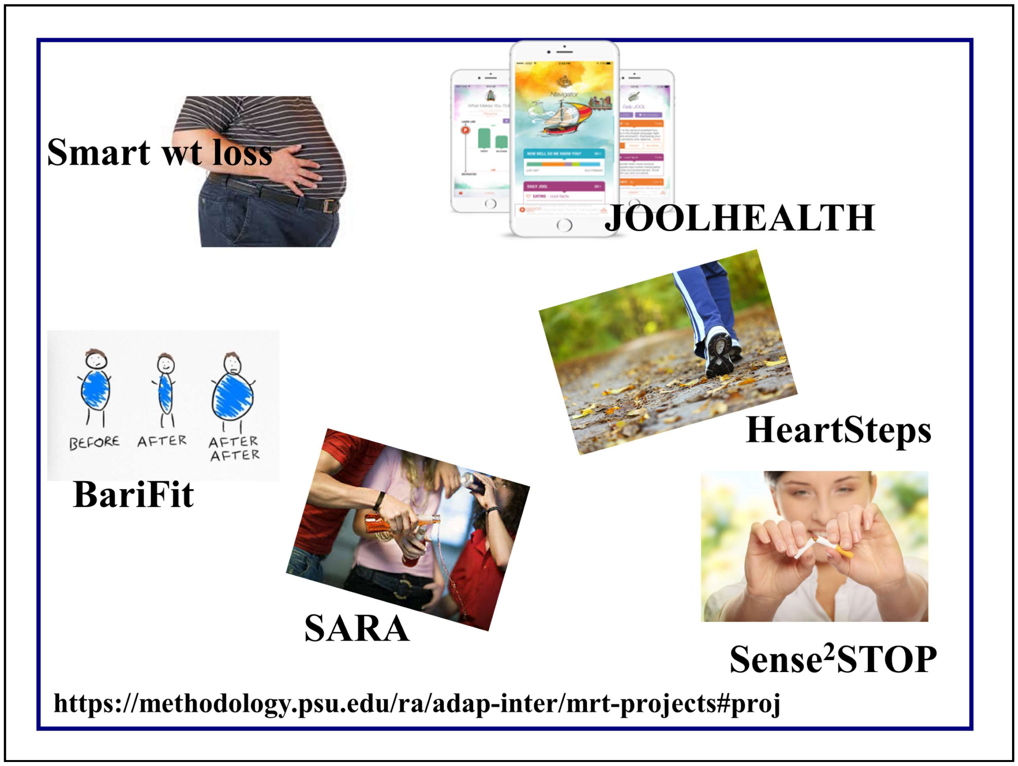
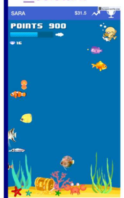

Smart wt loss
JOOLHEALTH
HeartSteps
BEFORE
AFTER
AFTER AFTER
BariFit
SARA
Sense^{2}STOP
https://methodology.psu.edu/ra/adap-inter/mrt-projects#proj

Mobile Intervention Components

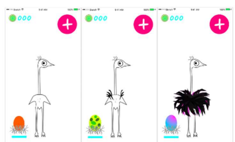
SARA
Substance
Abuse
Research
Assistant

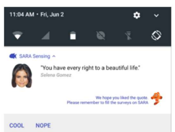
Optimizing mHealth Engagement



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?

5

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

blood pressure that falls in the stage 1 hypertension range

The systolic pressure is 140 to 159 mm Hg or your diastolic pressure is 90 to 99 mm Hg

Changing your lifestyle can go a long way toward controlling high blood pressure.

Eating a heart-healthy diet with less salt

Getting regular physical activity

Maintaining a healthy weight or losing weight if you're overweight or obese

Limiting the amount of alcohol you drink

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?

7

Activity suggestions are to help in your automated processing

Evening planning is to help in your reflective processing (controlled behavior)

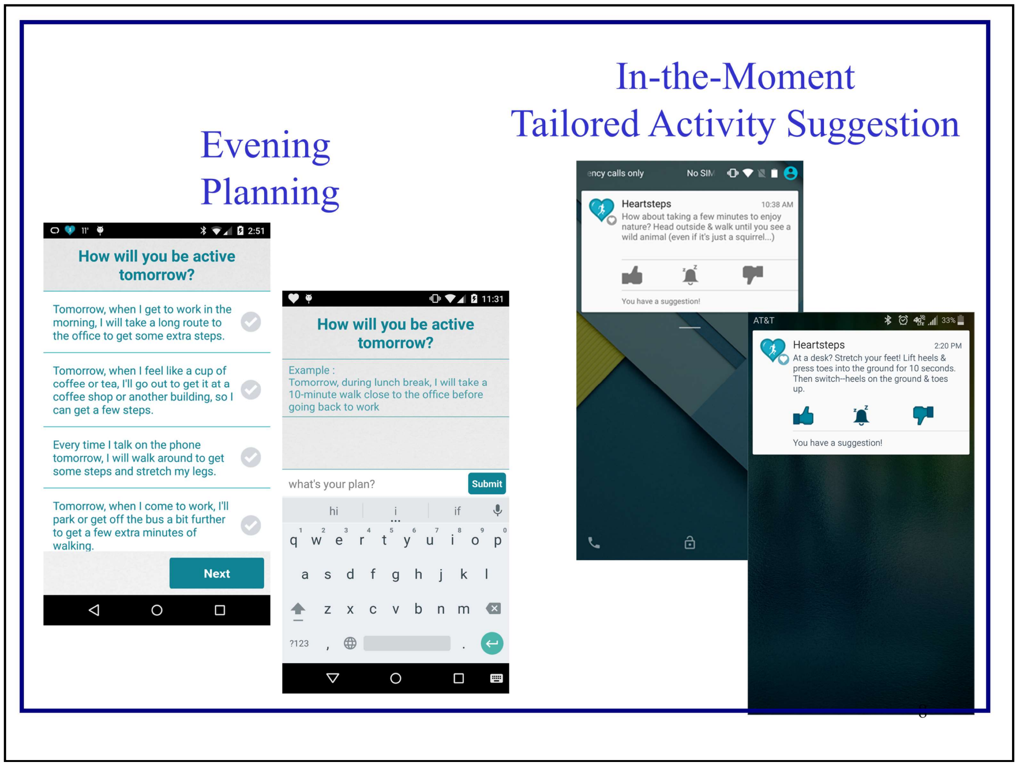
From grant proposal:

How those perceptions shift as people's goals and circumstances change over time has not been explored, however. Through the novel use of a micro-randomization methodology (see section C.3), this project will significantly advance the knowledge in this area by enabling us to analyze how the frequency and nature of different intervention components, such as prompts to self-monitor, planning activities, and activity suggestions displayed on the phone's lock screen influence, over time, not only physical activity but also user burden and engagement. Furthermore, the micro-randomization will facilitate generation and testing of theory-based hypotheses about how these effects of time-varying intervention components (e.g., whether or not to provide an activity suggestion), and their different doses, are moderated by aspects of the patients' lifestyle and context, such as the consistency in their physical-activity routines, work schedule, etc. In addition, we will employ novel learning algorithms to adapt and personalize when individual intervention components are displayed; these algorithms will explicitly take burden and engagement into account, aiming to maximize and maintain physical activity over longer time periods. Ours will be the first mHealth technology we know of that adapts to users' shifting perceptions of burden and value to keep them engaged with the system.

Theoretical innovation: There is growing evidence [12,61] that human behavior is governed both by *reflective processes*, like goal-setting and planning, and by *impulsive* or *automated processes*, like habits [127], emotional valuations [39], and priming [11]. Reflective processes are effortful, require attention, and unfold slowly, while automated processes are triggered by contextual cues and unfold efficiently without the need for attentional resources [120]. While reflective self-regulatory skills are a powerful tool for supporting behavior change, they have a downside, as the main self-regulatory intervention strategy. Human capacity for reflective, effortful self-regulation is limited and becomes likely to fail when a person's self-regulatory resources are depleted [90,115]. This is a reason why individuals attempting to diet or quit smoking often relapse at times of stress [90]. Lacking sufficient self-regulatory resources to deal both with stressors in their lives and with behavior-change efforts, people slip back into their habitual patterns that don't require cognitive effort. To counteract this shortcoming of reflective self-regulatory processes, we will specifically target automated self-regulatory processes as a key part of our maintenance intervention. This is a novel contribution because most mHealth interventions use reflective self-regulatory strategies almost exclusively [74]. As we discuss in section C1, in our proposed intervention we will leverage priming [11,35], evaluative conditioning [52], and implementation intentions [41,42] to help individuals engage in opportunistic physical activity and protect planned activities from being derailed when people are stressed, tired, or otherwise depleted. Ours is the first mHealth intervention we know of that supports automated self-regulation in such a comprehensive way.

Our second theoretical contribution is to investigate implementation requirements for reflective and automated self-regulatory strategies. For instance, we postulate that while automated self-regulatory intervention components can be highly valuable, if they are used too often, there is an increased likelihood that a person will habituate to them decreasing their effectiveness. To counteract habituation, there is an important theoretical need to identify when *not* to provide these automated cues to ensure continued potency of the signal. Similarly, although reflective self-regulatory techniques like planning can be burdensome, we postulate that it is important to identify opportunities when a person has the cognitive capacity to deeply engage in such reflective self-regulation. In this grant, we will utilize our novel micro-randomization study design to uncover conditions under which reflective and automated self-regulatory processes can be effectively deployed. It is possible, for instance, that the times of high stress and work load are when individuals stop using reflective components of an mHealth technology—leading to abandonment of tools that promote behavior change precisely when they are most needed. Our project will begin to uncover such relationships, advancing both behavioral theory and intervention design.

Finally, the inclusion of both reflective and automated self-regulatory strategies in the proposed intervention will enable us to investigate how patients' time-varying use of intervention features in different contexts affects their ability be remain physically active—providing potentially new insights about how reflective and automated self-regulation interact to support behavioral maintenance over time.



Activity suggestions are to help in your automated processing

Evening planning is to help in your reflective processing (controlled behavior)

Emphasize that there are many intervention components that make up a mobile health intervention.   We only experiment with a few.

Engagement strategies (e.g. to encourage self-monitoring or to encourage receptivity to treatment)

Some Treatment types behavioral, cognitive, motivational, social, self-monitoring, information

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

9

Much science goes into each part.

Structure of Mobile Health Intervention

1) Decision Points: times, t, at which a treatment might be delivered →"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

The momentary times were selected because these times are the times at which most people tended to have the greatest within person variance in activity
Pre-morning commute, mid-day, mid-afternoon, evening commute, after dinner.

Another example: The phone software monitors a risk measure at regular time intervals and if the risk measures hits a criterion then a treatment is provided.

For people who work, their available times are usually dictated by the constraints of the job, so we can have a good a priori sense of when they would have opportunities to walk. So, our original five decision points make a lot of sense. For retirees, their schedules might be much more variable, so we need to discover when the good times to intervene are. For them, much more frequent decision points make more sense. This may be the case for weekends even for employed people.

Structure of Mobile Health Intervention

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

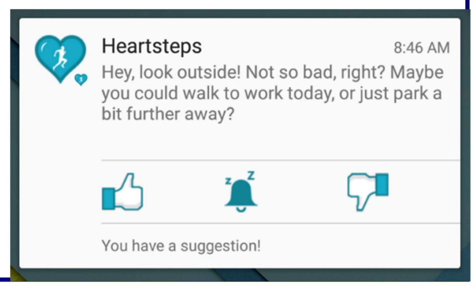
<u>HeartSteps</u>: classifications of activity, location, weather, step count, busyness of calendar, usefulness ratings, adherence…….

Can include time of day or day of week and present weather.

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)



Tailored based on location, time of day, day of week and weather

Delivery & User Acknowledgement: Suggestions were delivered to the user's lock screen. Upon delivery, the user would receive a notification that they had received a HeartSteps message; the phone would also vibrate and a blue LED on the front of the phone would flash. Users could access the suggestion by pulling down on the notification. Users could acknowledge the suggestion in one of three ways: (1) by giving the suggestion a thumbs-up rating, indicating that they saw the message and found it feasible and contextually appropriate; (2) by giving a thumbs-down rating, indicating a lack of either feasibility or context appropriateness; or (3) by "snoozing" (turning off) the suggestion delivery system for 1, 2, 4 or 8 hours. If the message was not acknowledged within 15 minutes, the system would send a reminder message. To ensure messages remained appropriate for the current context, suggestions timed out after 30 minutes and the lock screen notification disappeared.

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.

13

Availability is sensed pretreatment.

The momentary intervention can be turned off for 1-8 hours by the participant. The intervention is also off if the participant is currently active (e.g. walking) or if the participant may be driving a car

Available if

1. she is not currently in a car,
2. she is not currently walking, and
3. her phone is connected to the internet.

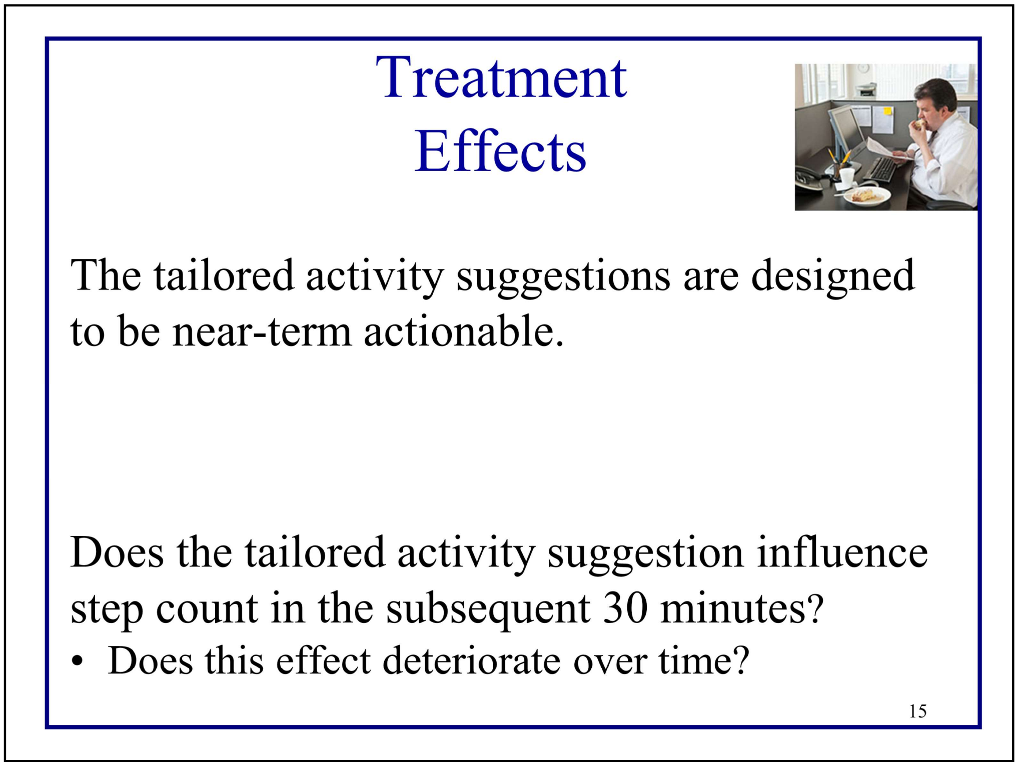
Adherence (i.e. compliance) is very different from availability. Suppose a person is available at a decision point. However the phone is in their purse across the room. So they don't hear whether the phone pings/ see the lockscreen light up. This person is non-adherent at this decision point. Primary analyses will be intention-to-treat and thus will average over non-compliance.

Structure of Mobile Health Intervention

4) Proximal Outcome Y_{t+1}

HeartSteps: Step count over 30 minutes following decision point, t

Frequently the actions are primarily designed to have a near-term effect on the individual. E.g. Help then manage current craving/stress, help them manage or be aware of the impact of their social setting on their craving/stress



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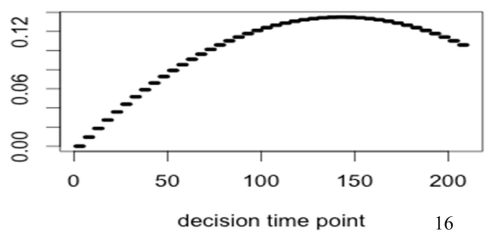
Treatment Effect

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

What does this effect mean?

Standardized Effect



16

Marginal over randomization treatment policy (and effects thereof), conditional on those who have intervention on.

The group who have the intervention turned on is a selected group of people likely depending on the intervention dose they experienced up to time j. This intervention dose \bar A_{j-1} may have caused burden, may have caused learning.

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

18

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)

19

We go through intuition that we have gained from analyses in which the treatment does not vary with time. Here the complication is that treatment is time varying. The issue is that both S_t and Z_t may be outcomes of past treatment.

Zj might include location, time of day, day of week, summaries of craving over prior hour, usual level of smoking at this time of day, etc. Might include features of time, j, so as to allow a more flexible model

S_j might be a vector as well and might include features of time S_j might be the output of a classifier

Conceptual Models

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

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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}
($Z_t \leftarrow$ sometimes called control variables)

20

j is the decision point, I am leaving off subject i subscript.

Zj might include location, time of day, day of week, summaries of craving over prior hour, usual level of smoking, prior activity level at this time of day, etc. Might include features of time, j, so as to allow a more flexible model

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.

21

These are the interpretations we know hold in cross-sectional analyses and in analyses in which the treatment does not vary with time.

Goal

- Develop data analytics 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

22

not so very independent, "independent" variables

“Centered and Weighted Least Squares Estimation”

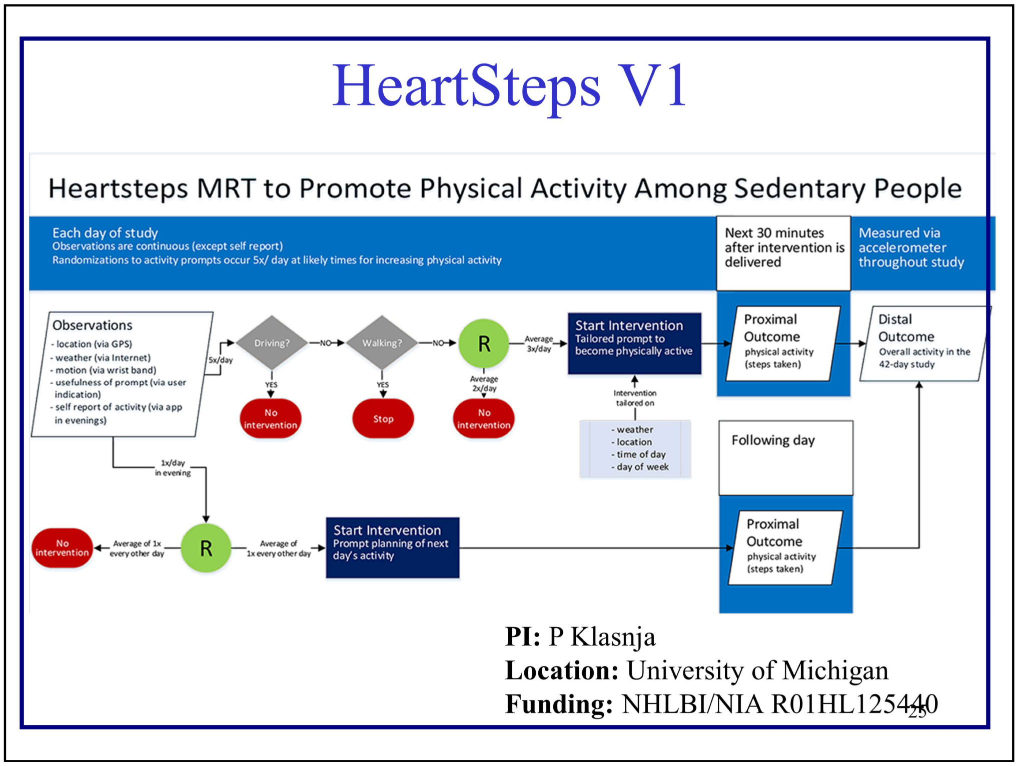
- Simple method for complex data!
- Enables unbiased inference for a causal, marginal, treatment effect (the β’s)
- Inference for treatment effect is not biased by how we use the controls to reduce the noise variance in Y_{t+1}

JASA, 2018

23

Application of the "Centered and Weighted Least Squares Estimation" method in the primary analysis of HeartSteps

24



This project tests the feasibility and effectiveness of providing, via a smartphone, just-in-time tailored physical activity suggestions as well as evening prompts to plan the following day's physical activity so as to help sedentary individuals increase their activity. The resulting data will be used to inform the development of a JITAI for increasing physical activity. 42 days; n=37

PI: Predrag Klasnja

Location: University of Michigan

Funding: NHLBI/NIA R01HL125440

heartsteps MRT
https://www.clinicaltrials.gov/ct2/show/NCT03225521?titles=HeartSteps&rank=1

Heartsteps

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

26

Delivery & User Acknowledgement: Suggestions were delivered to the user's lock screen. Upon delivery, the user would receive a notification that they had received a HeartSteps message; the phone would also vibrate and a blue LED on the front of the phone would flash. Users could access the suggestion by pulling down on the notification. Users could acknowledge the suggestion in one of three ways: (1) by giving the suggestion a thumbs-up rating, indicating that they saw the message and found it feasible and contextually appropriate; (2) by giving a thumbs-down rating, indicating a lack of either feasibility or context appropriateness; or (3) by "snoozing" (turning off) the suggestion delivery system for 1, 2, 4 or 8 hours. If the message was not acknowledged within 15 minutes, the system would send a reminder message. To ensure messages remained appropriate for the current context, suggestions timed out after 30 minutes and the lock screen notification disappeared.

Conceptual Models

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

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

27

Emphasize that d_0=0

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

28

.13 translates into a 14% increase over no treatment in step count about 33 steps
mean 30-minute step count is 253 steps

.51 translates into a 67% increase over no treatment in step count about 170 steps

Midway through study d_t=20 this increase has reduced to 16% increase in step count

Heartsteps

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

29

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

30

mean 30-minute step count is 253 steps

.21 translates into a 23% increase over no treatment in step count   about 59 steps

When d_t is added to the model one finds that initially beta0 coefficient of A1t=.729 and the coefficient of A1t*d_t is -.025

Pvalues for both are .000

.729 translates into a 107% increase over no treatment in step count   about 271 steps

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.

How did this effect the planning for HS V2?

We developed an engagement wrapper with a slicker UI

We developed a learning algorithm that should back off if the user's responsivity is decreasing.

This is based on posterior mean for the interaction with past dose. Weight this more heavily in determining randomization probability than the entire treatment effect.
If this interaction is negative, this is indicative of future deterioration.

Heartsteps

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

32

SA Murphy

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.

33

Usual step count is around 5000

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-- 34

In terms of the ability to obtain causal marginal effects and in terms of robustness.

SEMIPARAMETRIC GEE ANALYSIS IN PARTIALLY LINEAR SINGLE-INDEX MODELS FOR LONGITUDINAL DATA

BY JIA CHEN, DEGUI LI, HUA LIANG†,1 AND SUOJIN WANG‡,2 2015, Vol. 43, No. 4, 1682–1715

New Estimation and Model Selection Procedures for Semiparametric Modeling in Longitudinal Data Analysis, Jianqing FAN and Runze LI **Journal of the American Statistical Association**

September 2004, Vol. 99,pg. 710

References

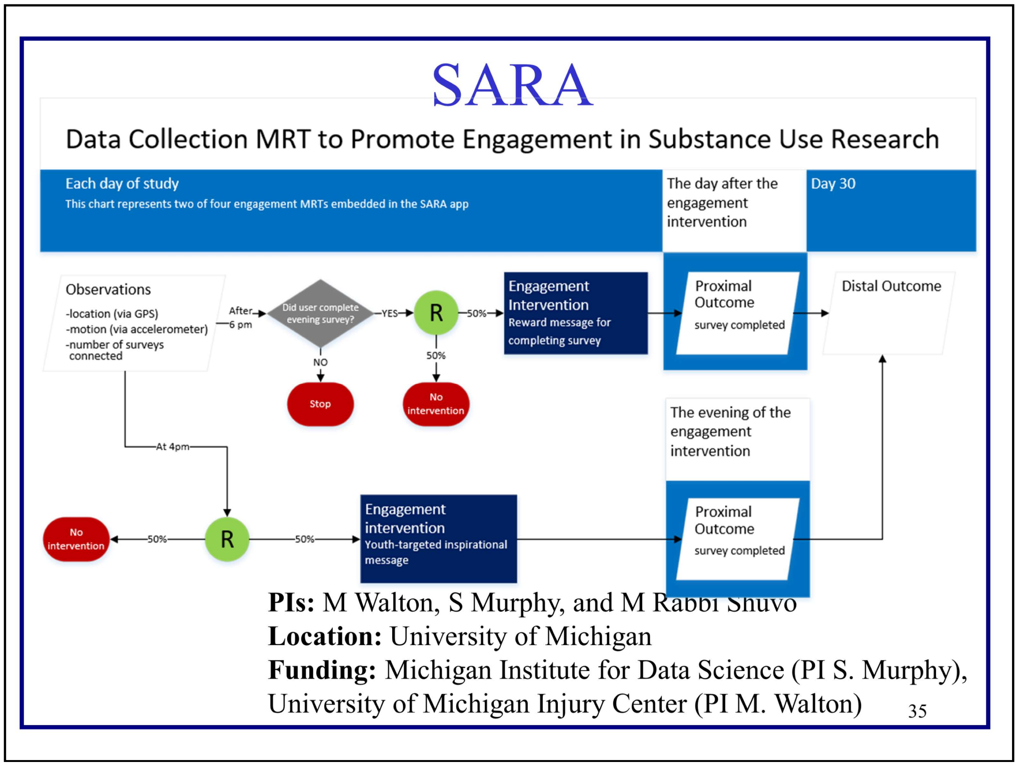
Intensive Longitudinal Methods by Niall Bolger and Jean-Philippe Laurenceau (2013)

Models for Intensive Longitudinal Data edited by Walls and Schaer (2006)

A Time-Varying Effect Model for Intensive Longitudinal Data by Tan et al., *Psychol Methods*. 2012 March ; 17(1): 61–77.

This last method does not have this problem as long as you do not include subject specific random effects. So TVEM without subject specific effects is not a problem

Dynamical systems analyses, e.g time series or pomps or mps



The Substance Abuse Research Assistance (SARA) is an app for gathering data about substance use in high-risk populations. App developers are using an MRT to improve engagement with completion of the self-report data collection measures. At the time this summary was written, this MRT is unique in that it has an engagement component, but not a treatment one. 30 days

PIs: Maureen Walton, Susan Murphy, and Mashfiqui Rabbi Shuvo

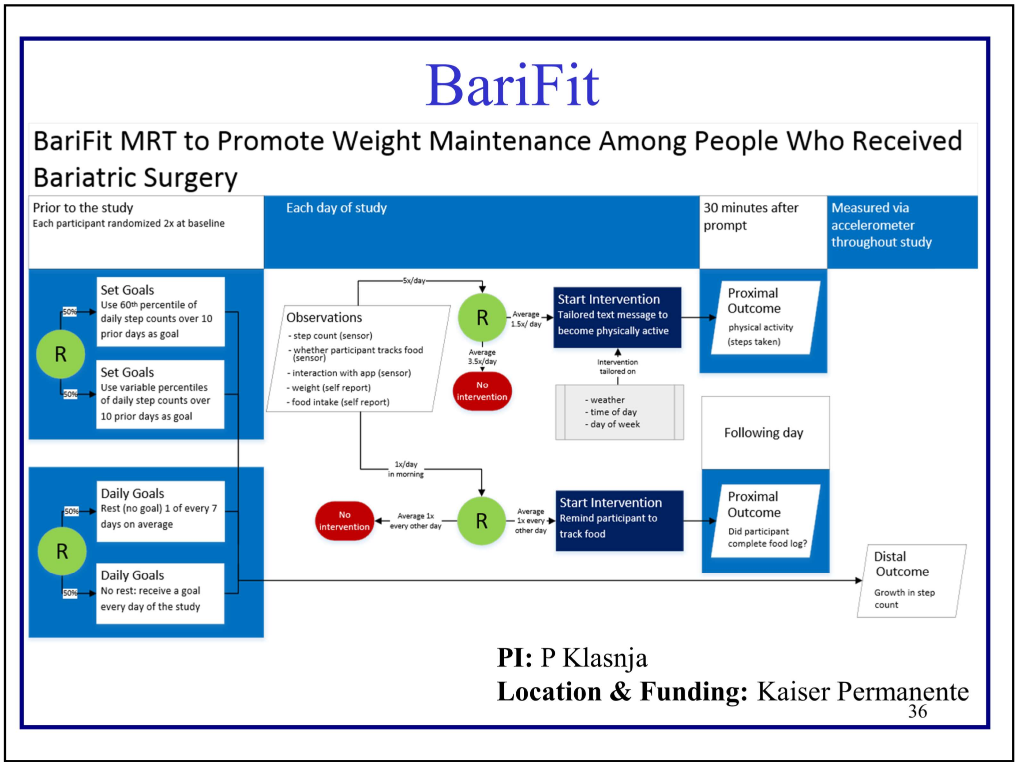
Location: Harvard University and University of Michigan

Funding: Michigan Institute for Data Science (PI S. Murphy), the University of Michigan Injury Center (PI M. Walton), NIDA P50 DA039838 (PI Linda Collins), NIAAA R01 AA023187 (PI S. Murphy), CDC R49 CE002099 (PI: M. Walton)

https://clinicaltrials.gov/ct2/show/NCT03255317

And

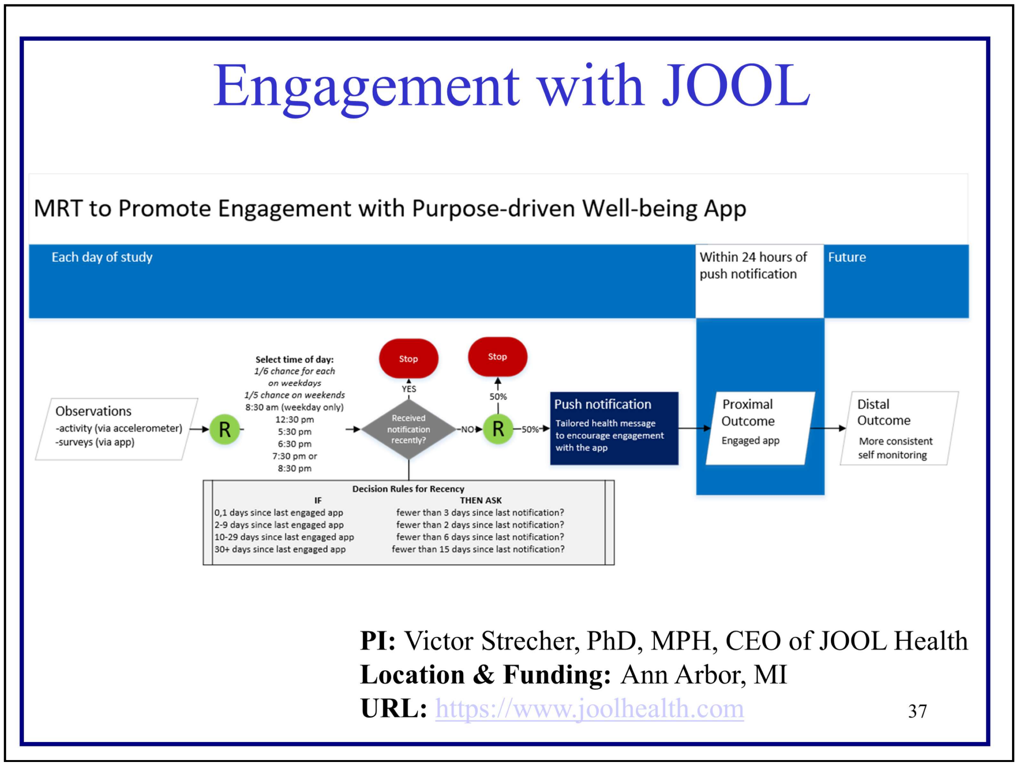
https://osf.io/whgfp/



Researchers are conducting this quality-improvement MRT aiming to promote weight maintenance through increased activity and improved diet among people who received bariatric surgery. At the time it was developed, this project was novel in that it implemented separate randomizations at the start of the study, on a daily basis, and five times throughout the day. N=50; 4months

PI: Pedja Klasna

Location & Funding: Kaiser Permanente

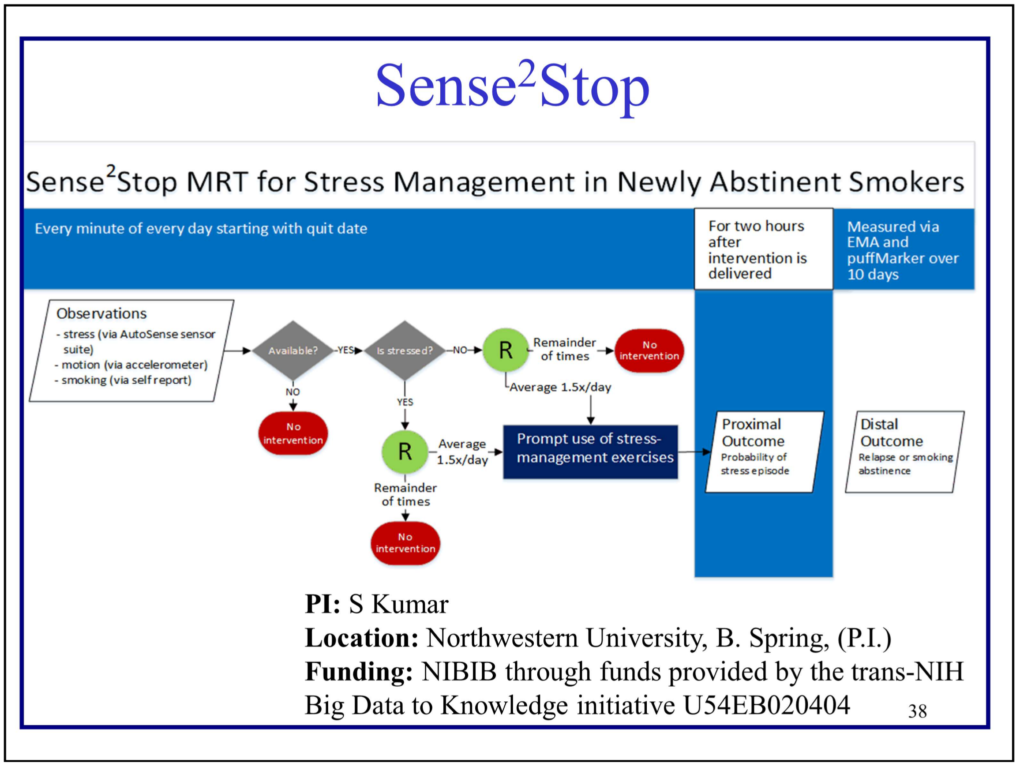


JOOL is a behavioral health and well-being app that is designed to help people monitor and improve their sleep, presence, activity, creativity, and eating, with the ultimate goal of helping people move closer to fulfilling their life's purpose. This MRT aims to understand whether push notifications of tailored health messages are useful in promoting engagement with the JOOL app; and, if so, when and under what circumstances they are most effective. 1,255 users of a commercial workplace wellbeing intervention product over 89 days

PI: Vic Strecher, PhD, MPH, CEO of JOOL Health

Location: Ann Arbor, Michigan

URL: https://www.joolhealth.com



This project tests the feasibility of conducting an MRT aiming to investigate whether real-time sensor-based assessments of stress are useful in optimizing the provision of just-in-time prompts to support stress-management in chronic smokers attempting to quit. The resulting data will be used to inform the development of a JITAI for smoking cessation. 10 days postquit, 4 days prequit.

PI: Santosh Kumar, Center of Excellence for Mobile Sensor Data-to-Knowledge (MD2K, https://md2k.org)

Location: Northwestern University, Bonnie Spring, (site P.I.)

Funding: NIBIB through funds provided by the trans-NIH Big Data to Knowledge (BD2K) initiative (www.bd2k.nih.gov). U54EB020404

MD2K smoking cessation study

https://www.clinicaltrials.gov/ct2/show/study/NCT03184389?recrs=a&lead=Northwestern+University&cntry1=NA%3AUS&state1=NA%3AUS%3AIL&draw=1

Collaborators!