Mobile Health Intervention Optimization

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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

BariFit

SARA

JOOLHEALTH

HeartSteps

Sense²STOP

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

**PUSH**

**PULL**
Example Pushes

In-the-Moment
Tailored Activity Suggestions
Optimizing mHealth Engagement

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

- 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 coronary artery disease

Three iterative studies:

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

How will you be active tomorrow?

Tomorrow, when I get to work in the morning, I will take a long route to the office to get some extra steps.

Tomorrow, when I feel like a cup of coffee or tea, I’ll go out to get it at a coffee shop or another building, so I can get a few steps.

Every time I talk on the phone tomorrow, I will walk around to get some steps and stretch my legs.

Tomorrow, when I come to work, I’ll park or get off the bus a bit further to get a few extra minutes of walking.

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In-the-Moment Tailored Activity Suggestion

Heartsteps

How about taking a few minutes to enjoy nature? Head outside & walk until you see a wild animal (even if it’s just a squirrel...)

You have a suggestion!

Heartsteps

At a desk? Stretch your feet! Lift heels & press toes into the ground for 10 seconds. Then switch–heels on the ground & toes up.

You have a 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

HeartSteps: 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)

HeartSteps: 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

HeartSteps: 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!

HeartSteps: Unavailable if sensors indicate that the individual may be operating a vehicle, is walking or has turned off the intervention.
4) Proximal Outcome $Y_{t+1}$

**HeartSteps**: Step count over 30 minutes following decision point, $t$
The tailored activity suggestions are designed to be near-term actionable: to impact activity in the near term.

Does the tailored activity suggestion influence step count in the subsequent 30 minutes?
• Does this effect deteriorate over time?
Effect of activity suggestion on step count is likely time-varying

What does this effect mean?

Treatment Effect

Standardized Effect
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:

\[ Y_{t+1} \sim \alpha_0 + \alpha_1^T Z_t + \beta_0 A_t \]

and then next,

\[ Y_{t+1} \sim \alpha_0 + \alpha_1^T Z_t + \beta_0 A_t + \beta_1 A_t S_t \]

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:

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and then next,

\[ Y_{t+1} \sim \alpha_0 + \alpha_1^T Z_t + \beta_0 A_t + \beta_1 A_t S_t \]

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

\[ Y_{t+1} \sim \alpha_0 + \alpha_1^T Z_t + \beta_0 A_t \]

\( \beta_0 \) is the effect, marginal over all observed and all unobserved variables, of the activity suggestion on subsequent activity.

\[ Y_{t+1} \sim \alpha_0 + \alpha_1^T Z_t + \beta_0 A_t + \beta_1 A_t S_t \]

\( \beta_0 + \beta_1 \) 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 $\beta$ coefficients

• Challenges:
  • Time-varying treatment ($A_t, t=1,...,T$)
  • “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 $\beta$’s)
• Inference for treatment effect is not biased by how we use the controls to reduce the noise variance in $Y_{t+1}$
Application of the “Centered and Weighted Least Squares Estimation” method in an initial analysis of HeartSteps
HeartSteps V1

Heartsteps MRT to Promote Physical Activity Among Sedentary People

Each day of study
Observations are continuous (except self report)
Randomizations to activity prompts occur 5x/day at likely times for increasing physical activity

Next 30 minutes after intervention is delivered
Measured via accelerometer throughout study

Observations
- location (via GPS)
- weather (via internet)
- motion (via wrist band)
- usefulness of prompt (via user indication)
- self report of activity (via app in evening)

Driving?    Walking?    Average 2x/day
No Intervention    Stop    No Intervention

Start Intervention
Prompt planning of next day's activity

Start Intervention
Tailored prompt to become physically active

Proximal Outcome
physical activity (steps taken)

Distal Outcome
Overall activity in the 42-day study

Following day

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

\[ Y_{t+1} \sim \alpha_0 + \alpha_1 Z_t + \beta_0 A_t \]
\[ Y_{t+1} \sim \alpha_0 + \alpha_1 Z_t + \alpha_2 d_t + \beta_0 A_t + \beta_1 A_t d_t \]

- \( t=1, \ldots, T=210 \)
- \( Y_{t+1} = \) log-transformed step count in the 30 minutes after the \( t \)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 prior to the \( t \)th decision point,
- \( d_t = \) days in study; takes values in \((0,1,\ldots,41)\)
HeartSteps Analysis

\[ Y_{t+1} \sim \alpha_0 + \alpha_1 Z_t + \beta_0 A_t, \text{ and} \]

\[ Y_{t+1} \sim \alpha_0 + \alpha_1 Z_t + \alpha_2 d_t + \beta_0 A_t + \beta_1 A_t d_t \]

<table>
<thead>
<tr>
<th>Causal Effect Term</th>
<th>Estimate</th>
<th>95% CI</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_0 A_t ) (effect of an activity suggestion)</td>
<td>( \hat{\beta}_0 = .13 )</td>
<td>(-0.01, 0.27)</td>
<td>.06</td>
</tr>
<tr>
<td>( \beta_0 A_t + \beta_1 A_t d_t ) (time trend in effect</td>
<td>( \hat{\beta}_0 = .51 )</td>
<td>(.20, .81)</td>
<td>&lt;.01</td>
</tr>
<tr>
<td>of an activity suggestion)</td>
<td>( \hat{\beta}_1 = -.02 )</td>
<td>(-.03, -.01)</td>
<td>&lt;.01</td>
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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

\[ Y_{t+1} \sim \alpha_0 + \alpha_1 Z_t + \beta_0 A_{1t} + \beta_1 A_{2t} \]

- \( A_{1t} = 1 \) 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,

<table>
<thead>
<tr>
<th>Causal Effect</th>
<th>Estimate</th>
<th>95% CI</th>
<th>p-value</th>
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</thead>
<tbody>
<tr>
<td>( \hat{\beta}<em>0 A</em>{1t} + \hat{\beta}<em>1 A</em>{2t} )</td>
<td>( \hat{\beta}_0 = 0.21 )</td>
<td>( (0.04, 0.39) )</td>
<td>.02 ns</td>
</tr>
<tr>
<td></td>
<td>( \hat{\beta}_1 &gt; 0 )</td>
<td>ns</td>
<td>ns</td>
</tr>
</tbody>
</table>
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 do not 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

Each day of study
This chart represents two of four engagement MRTs embedded in the SARA app

Observations
- location via (GPS)
- motion (via accelerometer)
- number of surveys completed

1/x day between 12 pm and 6 pm

Did user complete evening survey?

- YES
  - Reward message for completing survey
  - 50%

- NO
  - Stop
  - 50%

2R

Engagement intervention
Youth-targeted message encouraging completion of assessment later in the day

No Intervention

R

Proximal Outcome
survey completed

The day after the engagement intervention

Distal Outcome
Completion rate of surveys during study

The evening of the engagement intervention

Proximal Outcome
survey completed

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

Prior to the study
Each participant randomized 2x at baseline

Each day of study

30 minutes after prompt
Measured via accelerometer throughout study

Set Goals
Use 60th percentile of daily step counts over 10 prior days as goal

Observations
- step count (sensor)
- weight (self report)
- food intake (self report)

Average 1.5 x/day
5x/day

Start Intervention
Tailored text message to become physically active

Proximal Outcome
physical activity (steps taken)

Intervention tailored on

- weather
- time of day
- day of week

No intervention

R

Daily Goals
Rest (no goal) 1 of every 7 days on average

Average 1 x/day every other day

No intervention

R

Daily Goals
No rest: receive a goal every day of the study

Average 1 x/day every other day

Distal Outcome
Growth in step count

PI: P Klasnja
Location & Funding: Kaiser Permanente
Engagement with JOOL

MRT to Promote Engagement with Purpose-driven Well-being App

Each day of study

- Activity (via accelerometer)
- Surveys (via app)

Select time of day:
- 1/5 chance for each on weekdays
- 1/5 chance on weekends
- 8:30 am (weekday only)
- 12:30 pm
- 5:30 pm
- 6:30 pm
- 7:30 pm or 8:30 pm

Decisions:
- Received notification recently?
- Yes
- No

Stop

50%

Push notification
Tailored health message to encourage engagement with the app

Proximal Outcome
Engaged app

Within 24 hours of push notification

Future

Distal Outcome
More consistent self-monitoring

Decision Rules for Recency

<table>
<thead>
<tr>
<th>IF</th>
<th>THEN ASK</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-1 days since last engaged app</td>
<td>fewer than 3 days since last notification?</td>
</tr>
<tr>
<td>2-9 days since last engaged app</td>
<td>fewer than 2 days since last notification?</td>
</tr>
<tr>
<td>10-29 days since last engaged app</td>
<td>fewer than 6 days since last notification?</td>
</tr>
<tr>
<td>30+ days since last engaged app</td>
<td>fewer than 15 days since last notification?</td>
</tr>
</tbody>
</table>

PI: Victor Strecher, PhD, MPH, CEO of JOOL Health
Location & Funding: Ann Arbor, MI
URL: https://www.joolhealth.com
Sense^2 Stop

Sense^2 Stop MRT for Stress Management in Newly Abstinent Smokers

Every minute of every day starting with quit date

Available? NO

is stressed? NO

No intervention

Available? YES

is stressed? NO

Remainder of times

No intervention

Average 1.5x/day

Remainder of times

No intervention

Prompt use of stress-management exercises

Proximal Outcome
Probability of stress episode

Distal Outcome
Release or smoking abstinence

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!