Improving Mobile Health Interventions

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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

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...)

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!
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:
  o 42 day micro-randomized pilot study with sedentary individuals,
  o 90 day micro-randomized study,
  o 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

**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**

**Example:**
Tomorrow, during lunch break, I will take a 10-minute walk close to the office before going back to work.

**What’s your plan?**

Submit

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**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.
Structure of Mobile Health Intervention

4) Proximal Outcome $Y_{t+1}$

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

What does this effect mean?

Standardized Effect

decision time point
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 ($A_t$, $t=1,\ldots,T$)
  • “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 $\beta$’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

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

Observations
- location (via GPS)
- weather (via internet)
- motion (via wristband)
- usefulness of prompt (via user indications)
- self-report of activity (via app in evenings)

Next 30 minutes after intervention is delivered

Start Intervention
Tailored prompt to become physically active

Proximal Outcome
Physical activity (steps taken)

Distal Outcome
Overall activity in the 42-day study

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 before 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 of an</td>
<td>( \hat{\beta}_0 = .51 )</td>
<td>(.20, .81)</td>
<td>&lt;.01</td>
</tr>
<tr>
<td>activity suggestion)</td>
<td>( \hat{\beta}_1 = -.02 )</td>
<td>(−.03, -.01)</td>
<td>&lt;.01</td>
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</tbody>
</table>
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 \( \times \) 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>
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</thead>
</table>
| \( \beta_0 A_{1t} + \beta_1 A_{2t} \) | \( \hat{\beta}_0 = .21 \)  
\( \hat{\beta}_1 > 0 \) | (.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--
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 MRT to Promote Weight Maintenance Among People Who Received Bariatric Surgery

Prior to the study
Each participant randomized 2x at baseline

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

Set Goals
Use variable percentiles of daily step counts over 10 prior days as goal

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

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

Observations
- step count (sensor)
- whether participant tracks food (sensor)
- interaction with app (sensor)
- weight (self report)
- food intake (self report)

Start Intervention
Tailored text message to become physically active

Average 1.5k/day

Average 3.5k/day

No intervention

Start Intervention
Remind participant to track food

Average 1k/day every other day

Average 1k/day every other day

No intervention

Proximal Outcome
physical activity (steps taken)

Intervention

- weather
- time of day
- day of week

Following day

Proximal Outcome
Did participant complete food log?

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

<table>
<thead>
<tr>
<th>Each day of study</th>
<th>Within 24 hours of push notification</th>
<th>Future</th>
</tr>
</thead>
</table>

### Observations
- activity (via accelerometer)
- surveys (via app)

### Decision Rules for Recency

<table>
<thead>
<tr>
<th>IF</th>
<th>THEN ASK</th>
</tr>
</thead>
<tbody>
<tr>
<td>0+ 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>

### Flowchart

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

2. Received notification recently?
   - NO
     - 50% chance

3. Push notification
   - Tailored health message to encourage engagement with the app

4. Proximal Outcome
   - Engaged app

5. Distal Outcome
   - More consistent self-monitoring

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

For two hours after intervention is delivered

Measured via EMA and puffMarker over 10 days

Observations
- stress (via AutoSense sensor suit)
- motion (via accelerometer)
- smoking (via self report)

Available?
NO

is stressed?
NO

R

Remainder of times
No intervention

NO intervention

YES

Average 1.5x/day

R

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!