JITAI Development in Mobile Health

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

The Methodology Center
advancing methods, improving health

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Overview

- Session 1: Introduction to JITAIs: Just-in-Time Adaptive Interventions
- Session 2: Micro-randomized Trials for Developing mHealth JITAIs
- Session 3: Data Analytics for Developing JITAIs

Session 3: Data Analytics for Developing JITAIs

- Examples with Interesting Questions

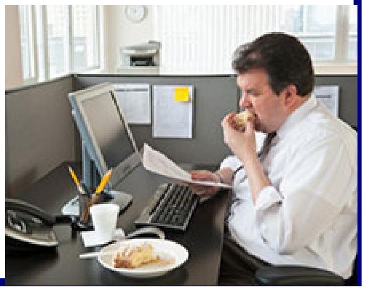
- Intensive Longitudinal Analysis Methods:
  - From ILD to ILID!

- BASICS Mobile

HeartSteps

Wearable activity-tracker + smartphone-based intervention to encourage physical activity

- Data: sensors provide activity, busyness of calendar, location, weather + self-report in eve.
- Decision points: 5x/day
- Treatments: deliver or do not deliver tailored activity recommendation on smartphone at each decision point
- Availability: not driving, not exercising, intervention is turned on
- Does recent physical activity or busyness of calendar influence the effectiveness of the activity recommendation?



Sense2Stop

Wearable chest-strap + wrist bands + access to smartphone stress-regulation apps to reduce stress and prevent relapse

- Data: sensors provide activity, stress, cigarette smoking, use of stress regulation apps + 4 self-report occasions
- Decision points: Every minute during 10 hour day
- Treatments: deliver or do not deliver via wristband “cue” to practice stress-regulation exercises
- Availability: not driving, intervention is turned on, ≥ 60min since last reminder, ≥ 10min since last self-report, classification of stress is possible
- Will delivering the cue to practice stress-regulation exercises be effective when the participant is currently stressed (or not-stressed)?

BASICS Mobile

Smartphone-based intervention to help college students reduce harm due to drinking and smoking

- Data: self-report data (3 x per day)
- Decision points: mid-day and evening
- Treatments: mindfulness-based message or general health info
- Availability: yes if answered self-report
- Is the effect of providing a mindfulness-based message on subsequent smoking moderated by an increase in the participant’s need to self-regulate?

Session 3: Data Analytics for Developing JITAIs

- Examples with Interesting Questions

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Data

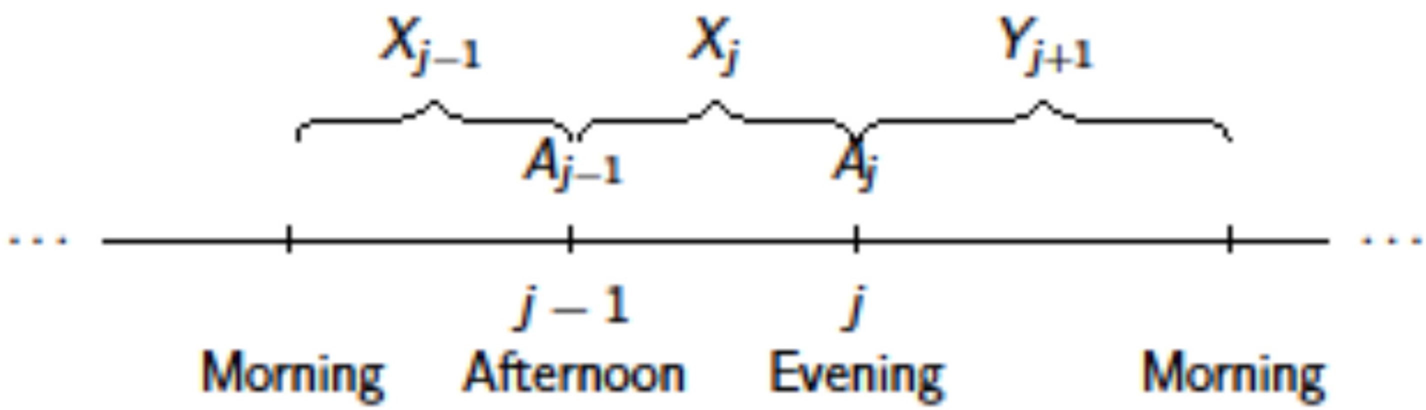
On each of n participants:

- $j=1,\ldots,J$ decision points
- X_j individual/contextual characteristics at decision point j
- I_j=1 if available, I_j=0 if not.
- A_j=1 if treated, A_j=0 if not treated at decision j.
- Y_{j+1} proximal response

$H_j=\{(X_i, I_i, A_i, Y_{i+1}), i=1,\ldots,j-1; X_j, I_j\}$ denotes participant history through j

Example Data Structure

BASICS Mobile



Common Intensive Longitudinal Analysis Methods

- GEE analyses
- Multilevel analyses
  - Time varying effect model analysis
- Dynamical systems analyses

--These analyses do not take advantage of the micro-randomization! Can accidentally eliminate the advantages of randomization for estimating causal effects--

Conceptual Models

Generally we fit a series of increasingly more complex models:

$$Y_{j+1} \sim a_0 + a_1^T X_j + a_2 A_j$$

and then next,

$$Y_{j+1} \sim b_0 + b_1^T X_j + b_2 A_j + b_3 A_j S_j$$

- $S_j = 1$ if currently stressed, and 0 otherwise
- Y_{j+1} is subsequent smoking rate
- $A_j = 1$ if delivered a mindfulness treatment and 0 otherwise
- X_j control variables from H_j, includes S_j

Interpretation

Series of models:

$$Y_{j+1} \sim a_0 + a_1^T X_j + a_2 A_j$$

and then next,

$$Y_{j+1} \sim b_0 + b_1^T X_j + b_2 A_j + b_3 A_j S_j$$

a_2 is the average effect (across time) of the mindfulness treatment on subsequent smoking rate

b_2 is the average effect (across non-stressed times) of the mindfulness treatment on subsequent smoking rate

$b_2 + b_3$ is the average effect (across stressed times) of the mindfulness treatment on subsequent smoking rate.

First Challenge

Both GEE and multilevel modeling estimation methods use an estimated correlation structure of the repeated proximal responses $\{Y_1, Y_2, Y_3, Y_4, \ldots, Y_{J+1}\}$ to construct $\hat{a}_2, \hat{b}_2, \hat{b}_2 + \hat{b}_3$

The use of the correlation structure destroys the marginal (average) interpretations of $\hat{a}_2, \hat{b}_2, \hat{b}_2 + \hat{b}_3$. The estimation (GEE, multilevel modeling) methods do not yield $\hat{a}_2, \hat{b}_2, \hat{b}_2 + \hat{b}_3$ with these interpretations.

Second Challenge

In many mobile health settings the randomization probabilities will depend on past participant history, e.g., $H_j=\{(X_i, I_i, A_i, Y_{i+1}), i=1,\ldots,j-1; X_j, I_j\}$

Again the estimation (GEE, multilevel modeling) methods do not yield $\hat{a}_2$, $\hat{b}_2$, $\hat{b}_2 + \hat{b}_3$ with the desired marginal (average) interpretations.

Simple Solutions!

- Use a working independence correlation matrix with the GEE

- Take advantage of the micro-randomization (next slide)

Standard Errors need adjustment. We have R software to do this.

Simple Solutions

Use a GEE analysis method with an independence working correlation matrix and with weight equal to availability, I_j.

Our interpretation of $\hat{a}_2$, $\hat{b}_2$, $\hat{b}_2 + \hat{b}_3$ is correct if:

1. the randomization probabilities are constant, OR

2. if the randomization probability depends at most on S_j and you replace A_j in your model by A_j - $p(S_j)$ in the model.

$p(S_j)$ is the probability that A_j is 1

Initial Solutions

OR

3. Most general method: use weights $(I_j)(w_j)$ where

$$w_j = \left(\frac{1}{p(H_j)}\right)^{A_j} \left(\frac{1}{1-p(H_j)}\right)^{1-A_j}$$

$p(H_j)$ is the probability that A_j is 1

Added Bonus

The interpretations:

a_2 is the average effect (across times) of the mindfulness treatment on subsequent smoking rate

b_2 is the average effect (across non-stressed times) of the mindfulness treatment on subsequent smoking rate

$b_2 + b_3$ is the average effect (across stressed times) of the mindfulness treatment on subsequent smoking rate.

are correct even if you mis-specify the influence of participant history, H_j, on Y_{j+1} in your model!

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BASICS Mobile Pilot Data

On each of *n=28* participants:

- Decision points: $j=1,\ldots, J=28$
- Individual/contextual characteristics: X_j includes (1) increase in need to self-regulate thoughts (yes/no), (2) current urge to smoke, (3) prior smoking rate,(4) time of day, (5) baseline smoking severity, (6) baseline drinking level, (7) age and (8) gender
- Proximal response: Y_{j+1} is smoking rate until next self-report.

BASICS Mobile Pilot Data

On each of $n=28$ participants:

- Decision points: $j=1,\ldots, J=28$
- Indicator of mindfulness treatments, A_j=1, if only general health then A_j=0.
  - The probability that A_j=1 depends on prior smoking rate, current urge to smoke and time in study.
- Proximal response: Y_{j+1} is smoking rate until next self-report.

BASICS Mobile Conceptual Model

$$Y_{j+1} \sim b_0 + b_1^T X_j + b_2 A_j + b_3 A_j S_j$$

$S_j = 1$ if there is an increased need to self-regulate thoughts and 0 otherwise at decision point j

X_j = (1) increase in need to self-regulate thoughts (yes/no), (2) current urge to smoke, (3) prior smoking rate,(4) time of day, (5) baseline smoking severity, (6) baseline drinking level, (7) age and (8) gender

BASICS Mobile
Pilot Study Analysis

Weighted GEE Analysis based on $n=28$ participants of

$$Y_{j+1} \sim b_0 + b_1^T X_j + b_2 A_j + b_3 A_j S_j, \quad j=1,\ldots J=28$$

Effect	**Estimate**	**95% CI**	**p-value**
Increase in need to self-regulate, $S_j=1$	$\hat{b}_2 + \hat{b}_3$ = -.05	(-2.0, 1.1)	0.553
No increase in need to self-regulate, $S_j=0$	$\hat{b}_2$ = -2.5	(-5.0, -0.1)	0.045

Taking Advantage of Micro-Randomization

- Randomization enhances:
  - Causal inference based on minimal structural assumptions
- Challenge:
  - Combine current science based structural assumptions + causal inference methods + micro-randomization to increase replicability of scientific findings.

Practice specifying your data analyses following your micro-randomized trial!

Some Questions:

1. Will your micro-randomization probabilities depend on an individual or contextual variables?
2. Recall $Y_{j+1} \sim b_0 + b_1^T X_j + b_2 A_j + b_3 A_j S_j$:
    1. What variables will be in X_j?
    2. What types of moderation analyses would you like to perform? That is, what potential tailoring variables will be in S_j?

Collaborators