Treatment Effect on Availability in Mobile Health

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Abstract

In mobile health (mHealth) for behavioral change and maintenance, interventions are frequent and momentary throughout a study. Typically, a great deal of individual and contextual information on patients is generated over time through a mHealth application. For the application to successfully deliver interventions to a patient, the patients themselves must be available to receive the mobile interventions and actively engage with them. However, the patients will sometimes be in a situation where they cannot or are not willing to engage with the interventions. We define "availability" as the opposite situation where users are available to receive interventions. A patient's availability varies over time and may be affected by prior interventions. It is important to understand the reason for a person's availability because it might be the cause and effect of each intervention. This poster introduces "availability" in terms of the HeartSteps study, which was designed to increase physical activity of sedentary people. To draw inference between previous interventions and availability we will explore statistical methods for binary outcomes and simulation results through a generative model.

An Overview of HeartSteps

Description of the HeartSteps study

The HeartSteps application is composed of two interventions. First, the evening planning intervention: every evening, each user may be prompted to develop a plan for the following day's physical activity. The second intervention consists of in-the-moment activity suggestions tailored to the individual and their contextual state. The application can deliver these suggestions (three times on average) at any of the five decision points throughout the day. The decision time points are as follows: morning commute, mid-day, mid-afternoon, evening commute, and post-dinner times. When a suggestion is delivered, the user's phone will play a notification sound, vibrate, light up, and display the suggestion on the phone screen. These suggestions encourage physical activity at the time point and are intended to have an effect (getting a person to walk) within the next 30 minutes.

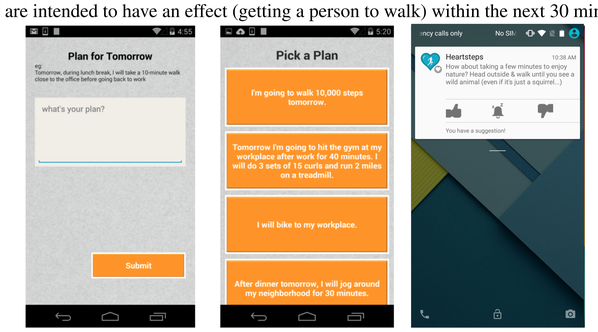

Figure 1: Example of HearSteps displays

Micro-randomized Trials Most mobile interventions are designed to be "**just-in-time**" interventions, meaning they provide treatments which help an individual make a healthy decision in the moment, such as engaging in a desirable behavior (e.g., taking a medication on time) or effectively coping with a stressful situation. As such, mobile interventions are often intended to have proximal, near-term effects.

Micro-randomized Trials (MRTs) involves randomly assigning an intervention option at each decision time point based on the participant's past behavior, past treatments and contextual variables. Since interventions are sequentially randomized throughout the conduct of the study, the number of interventions each participant receives may vary. MRTs is effective when we want to evaluate the efficacy of the application and to better understand which situations are optimal for intervention delivery.

Micro-randomized trials enable modeling of **time-varying causal effects or the effects moderated by variables of interest**. Therefore, Micro-randomized trials offer a way to optimize mobile interventions by utilizing the results obtained from the assessment of treatment effects.

Availability

The majority of data for a mobile health study is usually collected through a mobile application by utilizing a hardware such as a phone, wristband etc. The application makes use of mobile interventions, which are notifications sent to a user's device. Availability is important because before a mobile application can send these interventions it has to evaluate whether or not a user can actively engage with the intervention.

Availability is used by the mobile application to decide whether or not to send the intervention. If a patient is evaluated as "available" then the application will proceed to send an intervention usually randomized. If a patient is evaluated as "unavailable", then the application will not send an intervention.

A patient is considered available if they are not unavailable, which we define as follows for our study:

Unavailable:

- Due to Data Service (The patient does not have internet or data service)
- Due to Driving (The patient is driving an automobile)
- Due to Walking (The patient is already engaged in physical activity)

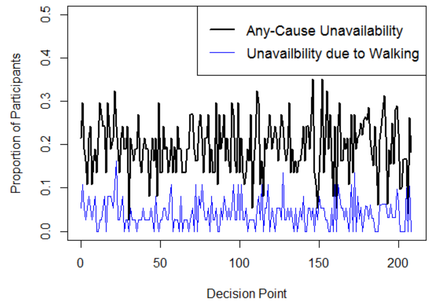

Figure 2: Proportion of participants unavailable either due to any cause or due to walking at each decision time point

Statistical Methods for Binary Outcomes

Multiplicative Structural Nested Mean Models (SNMMs) can be used if we are interested in the contrast of binary outcomes following treatments 1 or 0. If we are interested in proximal treatment effect, we can parameterize contrasts conditional on treatment and covariate histories through time t using log link as

$$log\left(E(Y_{t+1}|H_t, A_t = a_t)\right) - log\left(E(Y_{t+1}|H_t, A_t = 0)\right) = \gamma_t(H_t, A_t = a_t; \psi) \quad (1)$$

We can estimate the effect of relative risk by this parameterization. The most frequently used link for binary outcomes is logit link which enables us to estimate odds ratio. However, odds ratio cannot be estimated appropriately if you have multiple sequentially randomized interventions.

Under the assumption that the model for the treatment effect (1) is true, we can estimate this treatment effect as long as we know the randomization probability, which we always know in MRTs. However, If we want to estimate odds ratio under the assumption that model for the odds ratio is true, then we have to know $E(Y_{t+1}|H_t, A_t = 0)$. Knowledge of only the randomization probability does not guarantee the proper estimates for the odds ratio.

Treatment Effect on Unavailability due to Walking

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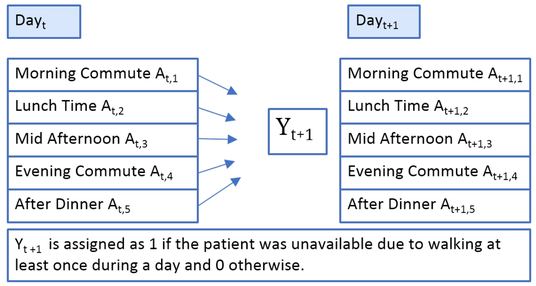

Figure 3: Data frame for a sequence of two days

- **Decision Time Points:** Decision time points are unique for each individual as the times are predetermined by the patients based on their own schedules.
- **Outcome of Interest:** We are mainly interested in the situation where a person's availability is classified as "unavailable due to walking". We are interested in an outcome that is an indicator of whether a person was "unavailable due to walking" at any of the five decision time points during a day.
- **Multiple Influences:** A person's availability can be influenced by many different variables such as the weather or location at the decision time point, religious holiday or vacation time etc.
- **Inference:** If we draw an inference such that previous treatments influenced a patient to be "unavailable due to walking" then we say the previous treatments had a positive effect on the patient's lifestyle.
- **Our Belief:** We believe that as number of treatments increase for an individual, their behavior is ought to adjust to the treatments so that they will become more physically active. Thus, resulting in more "unavailability due to walking".

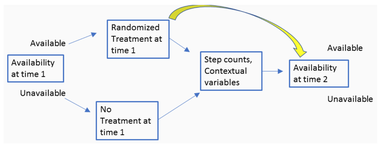

Figure 4: Diagram for a single decision time point

Future Plans

- Running simulations based on a proposed generative model. The model will initially only have one variable such as "weather" or some other exogenous variable.
- The simulation results will help us better assess our proposed generative model and also help us better understand why we cannot use certain statistical methods for our binary outcome analysis.
- The generative model will then be applied to a real data set (from the HeartSteps study) regarding sedentary people.
- In the future, the methods derived from our study will hopefully be used for studies regarding post-stroke patients.
- If the conclusions drawn from our study imply that treatment has a positive effect on patient lifestyle, then the mobile application was successful (in the context of our study).