Investigating the Relationship Between Dexcom Clarity Notification Settings and Change In Users’ Time-In-Range Over 90 Days

Annika Lee, Victor Wen, Xiaohan Liu
Advisor: Eli Ben-Michael  Client: Mark Derdzinski
Department of Statistics and Data Science, Dietrich College of Humanities and Social Science, Carnegie Mellon University, Pittsburgh PA

INTRODUCTION

Research Objective
- How do Dexcom Clarity notification settings correlate with changes in users’ Time In Range (TIR) levels?

Methods
- Multiple linear regression (MLR) with three way interactions
- Bootstrap pivotal 95% confidence intervals (CIs) used to provide uncertainty quantification on functions of coefficients

RESULTS

Figure 3: Pivotal 95% CIs for slope between notifications and change in TIR

Figure 4: Pivotal 95% CIs for intercept of notification status ON

DISCUSSION

- Associations for TIR notifications (mid level, positive; high level, negative), email report notifications (low level, negative), best day notifications (high level, negative)

- Lack demographic information of Clarity users (age, gender, diabetes duration, marital status, etc.) limited the ability to explain variability in change in TIR

Future Works
- Previous research suggested importance on demographic information - users who viewed their weekly TIR report with their family members showed greater improvements (Polonsky Et al.)
- Controlling for the demographic information of users in the model will likely provide more reliable estimates of associations between notification settings and improved diabetes management

REFERENCES

DATA DESCRIPTION

- Four datasets from Dexcom were matched by anonymized user ID and text entries were manipulated into one comprehensive aggregate dataset for analysis

METHODS

Subset Method
- For each notification type, users were categorized into four groups based on their notification status (‘On’ or ‘Off’) and the number of notifications (zero or greater than zero).
- Users’ TIR at the start of the 90 day period were dichotomized by quantile to form a categorical variable with levels (low, mid, high)

Table 2. Subsets of Users

<table>
<thead>
<tr>
<th>Type</th>
<th># Notifications = 0</th>
<th># Notifications &gt; 0</th>
</tr>
</thead>
<tbody>
<tr>
<td>ON</td>
<td>On-Zero</td>
<td>On-Greater</td>
</tr>
<tr>
<td>OFF</td>
<td>Off-Zero</td>
<td>Off-Greater</td>
</tr>
</tbody>
</table>

MLR Model with Three Way Interactions
- Including a three way interaction among starting TIR level, notification status, and number of notification received enabled separate analysis of users in each of the subsets and in different starting TIR levels by examining combinations of coefficient estimates for slope and intercept

For a fixed notification type, change in TIR is modeled as:

\[
\text{delta_TIR} = \beta_0 + \beta_1 \times \text{On} + \beta_2 \times \text{Zero} + \beta_3 \times \text{On} \times \text{Zero} + \beta_4 \times \text{On} \times \text{Greater} + \beta_5 \times \text{On} \times \text{Mid} + \beta_6 \times \text{Mid} \times \text{Zero} + \beta_7 \times \text{Mid} \times \text{Greater} + \beta_8 \times \text{Mid} \times \text{High} + \beta_9 \times \text{High} \times \text{Zero} + \beta_{10} \times \text{High} \times \text{Greater} + \beta_{11} \times \text{High} \times \text{Mid}.
\]

Bootstrap Pivotal 95% CIs
- Residuals clearly violated Normality assumption thus pivotal bootstrap intervals were used to provide uncertainty quantification for estimated regression coefficients and sums of coefficients of interest

REFERENCES