Diabetes Mobile Care: Visualization and Prediction of Data from Multiple Mobile Health Technologies

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Background

Patients with type II diabetes mellitus (T2DM) and their care providers are burdened with monitoring complex health data to manage the illness effectively. Patients with T2DM and their providers must monitor blood glucose and HbA1c, laboratory values, weight, medication adherence, and lifestyle behaviors for successful disease management. Because T2DM is an illness that requires daily management, the majority of care must be performed by patients themselves. Mobile health (mHealth) technologies have the potential to revolutionize self-management and personalized care for T2DM patients by reducing the risk of escalations through constant data monitoring via smartphone apps and other mobile technologies.

The addition of mHealth technologies increases the amount of complex health data that patients and providers have to synthesize and interpret meaningfully. User-centered visualizations simplify the interpretation process by presenting information in an accessible way. However, when assessing a typical electronic health record, basic patient data is rarely visualized. Particularly, there is a lack of intensive longitudinal data akin to the data generated by mobile health devices.

Methods

In this mixed-methods exploratory study, patients with T2DM (N=60), tracked data over 6 months using a phone-tethered glucometer, a cellular body scale, a wrist-worn accelerometer, and a medication adherence text message survey. Data generated from the devices are visualized and analyzed using emerging data science techniques. A subset of patients are interviewed (n=60 interviews) to discuss their challenges and successes in diabetes self-management, use of the devices, and to get feedback on data visualizations. We will conduct focus groups with clinicians to explore ways to use these data and integrate data into health systems and electronic health records in Fall 2018.

Results to Date

Year 1 focused on information technology development and database creation. We successfully pulled in streams of data across multiple mobile devices. This proved challenging because vendors structure data and software integrations differently. Nevertheless, we aggregated these data into a database and merged these data with electronic health record and survey data.

In Year 2 with IRB approval and informed consent, we recruited patients (N=60) from April - November, 2017 from primary care clinics. Of the participants, 47 (78%) had uncontrolled diabetes defined as an HbA1c >7.0 (mean 8.18). Demographics indicated that 43 (72%) were female, 36 (60%) identified as Black or African American, 21 (35%) identified as White; and 46 (60%) did not have a college degree. Participants monitored their diabetes-related data with the devices provided and transmitted them to our study team on a secure server.

Initial interviews (n=20) highlight that many participants do not have in-home internet, creating challenges with data visualization software (Tableau & R ggplot2) that is not always mobile-friendly. Figure 1 below shows some of the visualizations. Nevertheless, that has also generated great qualitative data and feedback on design, development, and methods. Interviews will be complete by August, 2018. Participants report success and challenges with using multiple devices – all of which have different data transfer capability (e.g., Bluetooth, direct tethering, cellular transmission), app connections, and charging needs.

In Year 3 ongoing with interviews, we are analyzing the intensive longitudinal mHealth data to see if we could predict a patient's future glucose levels based on their glucose trajectory.

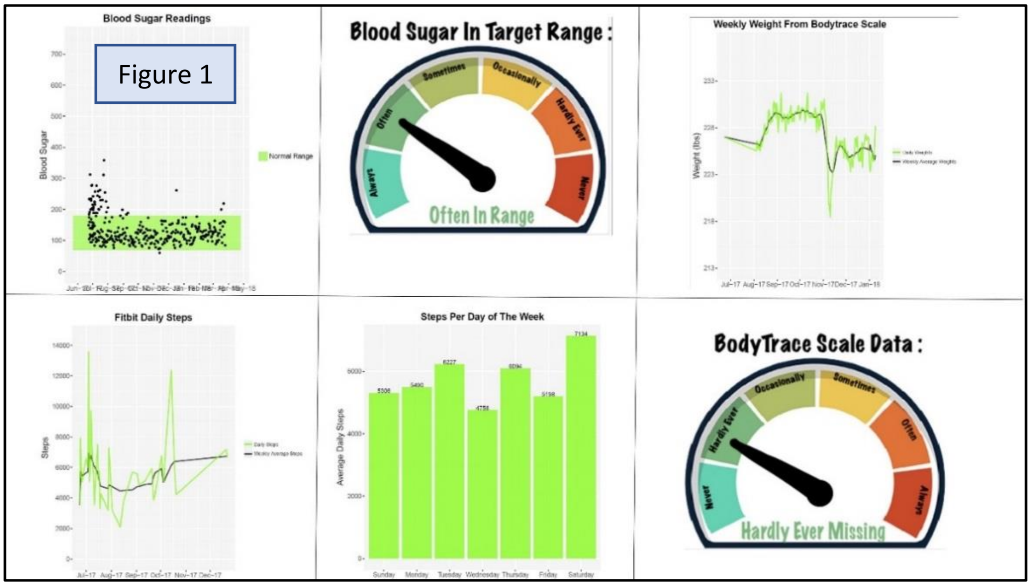
Discussion

Results indicate it is *feasible* for participants from *diverse* socioeconomic and racial backgrounds to track relevant diabetes-related data from multiple mobile health devices for at least 6 months. We retrieve streams of health-related data into a secure environment that can be used for data analyses and intervention. Many participants do not have in-home Internet with though access via smartphone. Initial interviews indicate participants find utility with the devices and are empowered to self-monitor. Participants are able to send us data over time, providing a more complete picture of their health in-between office visits. Our goal is to discover how to create appropriate data visualizations for providers, patients and to integrate these data streams into care delivery and health systems. Final data analysis will involve algorithm development from the collected data. Our goals are to create algorithms that can be leverage for both self-management in diabetes and for clinician management as well.

Design Challenge

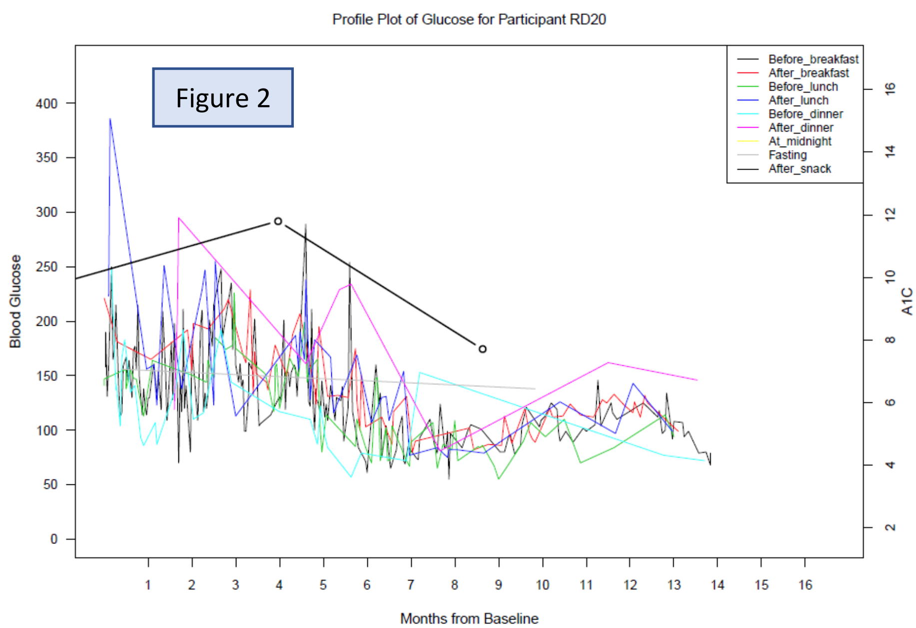
1) Combining streams of time intensive data from mobile technologies that patients from diverse background can understand.

Figure 1 shows is how we present various forms of data to participants from a phone-tethered glucometer, cellular-connected weight scale and a wrist-worn accelerometer. Optimal approaches to combine these data are needed whether that be on combined graphs or in a dashboard-like format



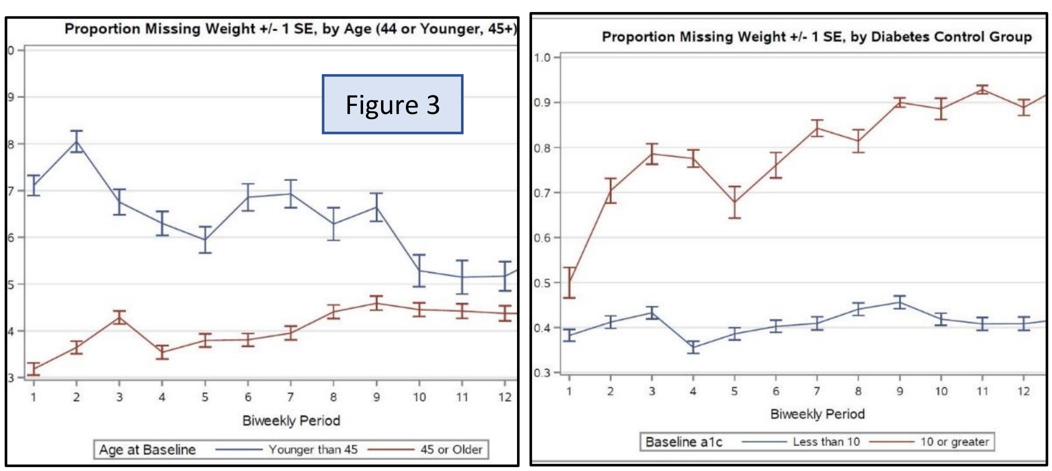
2) Visualizing predicted hemoglobin A1c (HbA1c) from daily blood glucose values.

Patient interviews suggest this may be one of the most powerful visualizations to present to patients. Current blood glucose to HbA1c conversions are based upon an average value of blood sugar taking 8 times daily. This does not reflect real life. We believe a cone shaped prediction of HbA1c with a numbered range should be presented to patients, yet are unclear as to the best approach to match this with real time blood glucose readings. A data visualization is developed by using a Shiny package in R to facilitate the modeling process. Figure 2 shows the blood glucose value measured at different time and the A1C value measure at baseline, 3, 6 and 9 months. This visualization will facilitate the process of developing a predictive model of A1C value.



3) Visualizing and combining multiple streams of “missingness” data in the electronic health record

Missing data gives information on patients and should be used as a tool alongside clinically transmitted data. Results show that we can use missing data as potential indicators of clinical need, real-time intervention to facilitate monitoring and healthy behaviors, and population-level trends such as seasonal effects. Figure 3 shows how missing data varies by severity of HbA1c and age (younger people enrolled tend to have higher HbA1c).



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