Empowering Patients Using Smart Mobile Health Platforms: Evidence From A Randomized Field Experiment

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Abstract

With today's technological advancements, mobile phones and wearable devices have become extensions of an increasingly diffused and smart digital infrastructure. In this paper, we examine the emerging mobile health (mHealth) platform and its health and economic impacts on the outcomes of diabetes patients. To do so, we partnered with a major mHealth firm that provides one of the largest mobile health app platforms in Asia, specializing in diabetes care, together with the Office of Chronic Disease Management from the national Ministry of Health. We designed and implemented a randomized field experiment based on 9,251 unique responses from 1,070 diabetes patients over a 15-month period from May 1, 2015, to July 31, 2016. Our main findings show that adoption of an mHealth platform by users has a statistically significant impact on reducing blood glucose and glycated hemoglobin levels, hospital visits, and medical expenses of diabetes patients over time. In conjunction with patient self-management through the mHealth platform, we also find heterogeneous effects between personalized and non-personalized messages. Interestingly, non-personalized mobile messages with general diabetes-care guidance demonstrate a stronger impact on patient health improvement. Our findings indicate the potential value of mHealth technologies, as well as the importance of mHealth platform design in achieving better healthcare outcomes.

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1. Introduction

With the technological advancements and the diminishing cost of IT infrastructure, societies today are increasingly characterized by an "Internet of Things (IOT)," a ubiquitous network of connected and smart devices. We see such examples in hospitals, malls, airports, cities, and many other contexts. Smartphones and tablets have become extensions of an increasingly smart digital infrastructure, and are having profound implications for business and society. We are witnessing a paradigm shift across many industries in today's world, in the way humans behave and communicate, as well as how governments, institutions, and organizations work. Such new technology today also demonstrates great potential in shaping individual behavior and decision making, in particular, through persuading individuals to modify behaviors to comply with a new set of behavioral norms necessary to attain goals.

Among many others, the healthcare industry stands at the societal frontier of this technological revolution (Topol 2013, Schwab 2016). Facilitated by emerging smart mobile health (mHealth) technologies, the healthcare ecosystem is currently undergoing a disruptive, digital transformation in transitioning from reactive care to proactive and preventive care that can potentially be administered more cost-effectively (Wactlar et al. 2011). As defined by Estrin and Sim (2010), mHealth is the combination of mobile computing, medical sensor, and communications technologies used for healthcare services, including chronic-disease management and wellness. mHealth includes medical applications that may run on smartphones, tablets, sensors that track vital signs and health activities, and cloud-based computing systems for collecting health data. As characterized by Eric Topol in his recent book, *The Creative Destruction of Medicine*, mobile devices and wireless sensors combined with cloud-based computing power are collectively transforming old medicine into new, individualized medicine by digitizing human beings (Topol 2013).

Indeed, mHealth technologies have demonstrated tremendous potential in shaping the healthcare industry toward a new era of evidence-based medicine and "Quantified Self" (QS)—individuals engaged in the self-tracking of biological, physical, behavioral, and environmental information (e.g., McKinsey 2013, Clark 2014). According to the US Food and Drug Administration (FDA), by 2018, 50% of the more than 3.4

billion smartphone and tablet users will have downloaded mHealth applications.[2] Moreover, a recent study by Grand View Research showed the global mHealth market will reach $49 billion by 2020, growing at a rate of more than 47% between 2013 and 2020.[3] To date, the increasing deployments of mHealth solutions are enabling the capture, integration, and analysis of critical interactions between the patient, care providers, and health system in an attempt to provide a continuum of patient care (Wactlar et al. 2011). Through mobile messaging and mobile applications, patients can receive at any time and any place health information that is targeted toward them and is delivered instantly; they can also share information with their healthcare providers. Moreover, dramatic improvements in mobile technologies allow patients to search for information, respond to information, and make decisions wherever they are and whenever they want. For patients, such increased mobility is not simply untethered computing; it means bringing new information sources, social communication, data processing, and health recommendation into their daily life 24/7. The increased mobility, informational capability, and pervasiveness of the mHealth technologies could have a profound healthcare impact on patients and care providers. Such smart and connected mHealth infrastructures can be especially helpful for chronic-disease care that often happens outside the traditional clinical care delivery settings (Phillips and Bazemore 2010). For example, mHealth applications (apps) created to help improve type 1 diabetes or type 2 diabetes care are perceived by their visionaries and programmers as game-changing tools that assist in the rigorous demands of diabetes self-management (e.g., Lee 2014).

Although mHealth applications and the IOT have the potential to perform real-time tracking of vital statistics and medical conditions to facilitate disease management and patient education, they also raise some challenges and opportunities for providing significant value to patients, providers, health systems, and society as a whole (McKinsey 2013, Clark 2014). In particular, a major challenge today is that from a patient's health and behavioral perspective, very little knowledge has been developed toward evaluating the effectiveness of the mHealth applications (e.g., Lee 2014, Agarwal et al. 2010). Uncertainty exists regarding whether mHealth can indeed improve patient health and behavior outcome. First, although mHealth technologies can facilitate easy medical communication and interventions for patients, too frequent interventions might lead to

[2] http://www.fda.gov/MedicalDevices/DigitalHealth/MobileMedicalApplications/default.htm
[3] http://www.grandviewresearch.com/industry-analysis/mhealth-market

annoyingness or habitation (Pop-Eleches et al. 2009). Second, the increased informational capability that mHealth technologies enable can lead to potential information overload due to users' cognitive constraints (Iyengar and Lepper 2000, Ghose et al. 2014). Besides, health information that is inconsistent with patients' prior belief or perceived as non-credible may be less persuasive and lead to potential information avoidance (Klein and Stefanek 2007, Harle et al. 2008, Harle et al. 2012). Third, the increased pervasiveness of personal behavioral tracking may bring potential privacy concerns to the users. Previous studies show patients might perceive highly personalized mobile SMS messages as intrusive (e.g., Pop-Eleches et al. 2009), and personalization might not work universally, because of the perceived privacy risk (e.g., Goldfarb and Tucker 2011). In addition, despite the increasing popularity of the mHealth technologies, existing platforms suffer from the lack of established regulations (McKinsey 2013, Clark 2014). This issue becomes especially critical today as more and more patients are using such applications. Finally, from a methodological perspective, measuring the effectiveness of mHealth technology on patient health and behavior outcomes can be rather challenging. Archival analyses using secondary data may not work due to the potential patient self-selection bias in mHealth technology adoption, as well as patient heterogeneity and high dropout rate in mHealth technology usage. Hence, these issues call for a scientific, rigorous approach to evaluate and quantify the effectiveness of the mHealth platforms.

The above challenges motivate us to ask the following research questions in this paper: *How can emerging technology persuade individuals to modify behaviors to comply with a new set of behavioral norms necessary to attain goals?*[4] *More specifically, in the context of healthcare, how can mHealth technology persuade patients with chronic diseases to make behavioral modification to comply with therapy, and what is the corresponding impact on patients' healthcare outcomes?* In particular, the healthcare outcomes we are interested in include patients' health behavior and health outcome over time, as well as patients' hospital visits and medical expense over time. We aim to explore whether smart mHealth platforms can empower patients with self-efficacy and facilitate patients' self-management with the chronic diseases. We are also interested in examining whether the mHealth platforms can help reduce patients'

[4] We thanks Professor Arun Rai for suggesting this framing.

hospital visits and medical expenses and thereby affect the operational costs of patients and healthcare providers.

To achieve our goal, in this paper, we instantiate our study within the context of mHealth application for diabetes care. The reason for choosing this research context is that diabetes is a chronic illness with significant health consequences that lead to macro- and microvascular complications, including heart disease, stroke, hypertension, nephropathy, and neuropathy. The American Diabetes Association (ADA) estimates that 25.8 million children and adults in the United States in 2011 had type 1 or type 2 diabetes. Diabetes poses a heavy economic burden on the US health care system, with estimated associated costs in 2007 of $174 billion (CDC 2012). Diabetes also imposes a severe impact on other parts of the world. For example, it affects more than 114 million Chinese (11.6% of the adult population, the highest in the world)[5] and 60 million people in the European region. Worldwide, high blood glucose kills about 3.4 million people annually. WHO projects diabetes deaths will double between 2005 and 2030.[6] Therefore, proper patient education and self-management are pivotal, especially for those who are unable to adhere to the complex treatment regimen. However, self-management tasks such as regular medication and insulin use, frequent blood sugar checks, strict diet management, and consistent exercise can be quite challenging. Hence, the potential for mobile and IOT technologies, specifically mHealth applications (apps), to help improve patients' adherence to these behaviors through long-term engagement is great. Nevertheless, beyond diabetes care, our methodologies and insights have the potential to be generalized to other chronic disease or wellness contexts as well.

In particular, to evaluate the effectiveness of mHealth applications on diabetes patients' behavior and health outcomes, we partnered with a major mHealth company in Asia that provides the nation's largest mHealth app platform that specializes in diabetes care, together with the Office of Chronic Disease Management from the national Ministry of Health. We designed and implemented a randomized field experiment based on 9,251 unique responses from 1,070 diabetes patients over a 15-month period from May 1, 2015, to July 31, 2016. By randomly assigning patients to different groups (e.g., adoption vs. no adoption of

[5] http://www.counterpunch.org/2015/07/24/the-increasing-burden-of-diabetes-in-china/
[6] http://www.euro.who.int/en/health-topics/noncommunicable-diseases/diabetes/data-and-statistics

mHealth application), we are able to measure the treatment effect from a causal perspective. Moreover, to evaluate the potential economic impact of the mHealth platform on patients' medical costs and hospital visits, we conducted additional surveys and telephone interviews before and after the experimental period.

Our main findings are as follows. *First*, the adoption of the mHealth platform demonstrates a statistically significant impact on reducing the blood glucose and glycated hemoglobin levels[7] of diabetes patients over time. *Second*, the mHealth platform shows a 21.6% stronger impact on patients' health outcome than does the web-based platform (i.e., PC version of the application) that provides the same functions for diabetes management. This finding builds on the prior literature on the differences between PC and mobile devices (e.g., Xu et al. 2016), indicating an edge that mobile devices have over PC in affecting patients' health behavior because mobility allows a user to respond more flexibly to real-time information (Ghose et al. 2013). *Third*, in conjunction with patient self-management through the mHealth platform, we also find heterogeneous effects between personalized and non-personalized messages. Interestingly, paired with all the health-management functions and resources provided by the mHealth platform, non-personalized SMS message interventions with general guidance about diabetes care demonstrate on average the highest effect on reducing patient glucose over time, 18.2% higher than personalized SMS message interventions with patient-specific medical guidance and 7.9% higher than no mobile message intervention at all. This finding is surprising and suggests personalized messaging may not always work in the context of mHealth, and the design of the mHealth platform is critical in achieving better patient health outcomes. *Finally*, our results also show the mHealth platform can have a statistically significant impact on reducing hospital visits and medical expenses for diabetes patients over time. Overall, our study has demonstrated a positive effect from the adoption of an mHealth app platform on improving diabetes patients' wellness and healthcare outcomes.

The major contributions of our study are as follows. *First*, to the best of our knowledge, our study is among the first research to examine the effectiveness of the mHealth application platform on chronic-disease management. We demonstrate the potential of the mHealth platform in facilitating patient empowerment and self-management for chronic diseases such as diabetes. *Second*, by partnering with a major mHealth platform

[7] Glycated hemoglobin is a form of hemoglobin that is measured primarily to identify the three-month average blood glucose concentration.

as a real-world testbed, we design and conduct a randomized field experiment over a total period of 15 months. This step enables us to identify and measure the impact of mHealth on patient health from a causal perspective, by eliminating the potential self-selection bias in mHealth technology adoption. *Third*, this study also presents a unique opportunity to examine the potential economic impact of mHealth and IOT technologies on the efficiency of healthcare management. *Fourth*, our research provides important insights on mHealth platform design through a better understanding of patient health behavior and interactions with the platform. Such knowledge can be highly valuable for healthcare mobile platform and IOT designers and policy makers to improve the design of smart and connected health infrastructures through sustained usage of the emerging technologies.

The rest of this paper is organized as follows. Section 2 discusses the related literature. Section 3 describes in detail how we design the randomized field experiments and how we partner with the real-world testbed to carry out the experiment on a large scale. Section 4 describes the experimental data. Section 5 discusses how we analyze the data as well as our final results. Finally, Section 6 concludes with potential future directions.

2. Literature Review

2.1 Impact of Healthcare IT

Our work is related to prior literature on the impact of healthcare IT. Recently, with the development of healthcare IT technologies and digital platforms, researchers have looked into the digital transformation of healthcare (e.g., Agarwal et al. 2010). Recent work has looked into the impact of healthcare IT,[8] including the associated efficiency and financial performance (e.g., Ayal and Seidmann 2009, Hitt 2010, Angst et al. 2011, Hydari et al. 2015), adoption of healthcare IT (e.g., Bhattacherjee et al. 2007, Angst et al. 2010), and the consumer perspective of healthcare IT (e.g., Agarwal and Khuntia 2009). Interestingly, the evidence thus far for the impact of healthcare IT on performance is equivocal, with prior research reporting positive, negative, and nonexistent effects (Agarwal et al. 2010). These discrepant findings call for plausible explanations and

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[8] For survey of recent work on the impact of healthcare IT, please refer to, for example, Goldzweig et al. (2009) and Dorr et al. (2007).

present important opportunities for further work. More recently, studies have also focused on the internet, social media, and healthcare (e.g., Kane et al. 2009, Gao et al. 2012, Gary et al. 2015). For example, using data from RateMDs.com, Gao et al. (2012) examined the trends in patients' online ratings for physicians over time and across specialties to identify what physician characteristics influence online ratings, and to examine how the value of ratings reflects physician quality. Gray et al. (2015) have examined the relationship between the online patient rating platform and the traditional quality measures of clinical and patient experience for physicians, and find no significant evidence that physician website ratings are associated with clinical quality measures. Our study builds on this prior set of literature on the impact of healthcare IT, and distinguishes itself by focusing specifically on the context of mHealth.

2.2 Mobile Health (mHealth) and User Behavior

Our paper is also related to the recent work on mHealth and how it can change user behavior and adherence to medical treatment. Several recent studies have successfully piloted programs based on mobile SMS text messages, targeting patients with asthma, obesity, smoking, HIV/AIDS, and diabetes (e.g., Krishna et al. 2009, Lester et al. 2010, Pop-Eleches et al. 2011, Nundy et al. 2014). They have found an impact from mobile SMS messaging on user health behavior; however, the content, intensity, and delivery mode of the SMS messaging seem to have a significant influence on the effectiveness of the mHealth interventions (Free et al. 2013). For example, Pop-Eleches et al. (2011) conducted a randomized trial using mobile SMS interventions in Kenya to test the effect of mobile SMS reminders on the adherence to HIV treatment. They found simple weekly reminder messages (without any additional counselling) can significantly improve adherence. But surprisingly, more frequent daily messages do not improve patient adherence, because of potential habituation or intrusion. They also found adding more personal words, such as words of encouragement, in the longer text messages was not more effective than either a short reminder or no reminder.

More recently, studies have looked at the stand-alone mHealth app as tools for user health self-management (e.g., Maged et al. 2014). For example, Demidowich et al. (2012) have surveyed the existing diabetes apps on the Android platform and found they offer a variety of functions, including self-monitoring blood glucose recording, medication or insulin logs, and prandial insulin dose calculators. Nes et al. (2012) studied the development and feasibility of intervention for diabetes patients with diaries and situational feedback via smartphone apps, which integrated communication between patients and a healthcare provider, allowing for the patient to log blood sugars, daily eating behaviors, medication compliance, physical activity and emotions into the mobile diary. Then a remote therapist with access to these diaries would formulate personalized feedback to the patient. In addition, the greatest number of apps belong to the exercise, weight loss, and wellness category. The built-in camera, standard in smartphones today, allows users to record a photo diary of daily food and drink (Maged et al. 2014). Lin et al. (2016) have studied the impact of mobile-based visual diaries and peer engagement through the app "MyPlate" on user eating behavior. The authors have found a strong positive impact of the mobile-based visual diary and dietitian support on improving customer engagement. Using a unique dataset from a freemium mobile weight management application, Uetake and Yang (2017) have investigated the role of short-term goal achievement on long-term outcomes and future customer development under the context of weight loss. They have also found the impact of short-term goal achievement varies across user segments. Compared with these recent studies, our work distinguishes itself in its focus on understanding the *causal* impact of the adoption of mHealth app on chronic disease care (particularly diabetes), with regard to patient behavior, medical expense, and health outcome.

2.3 Platform and Mobile App Market

In addition, our study is related to prior research on platform strategy (e.g., Eisenmann et al. 2011, Zhu and Iansiti 2012) and multi-sided market (e.g., Tilson et al. 2010, Parker and Van Alstyne 2014, Anderson et al. 2014). Recently, research in this area has been focused on information infrastructure studies (e.g., Hanseth and Lyytinen 2010), platform economics and governance (e.g., Eisenmann et al. 2011, Tiwana 2015), and platform evolution (e.g., Tiwana et al. 2010). Moreover, our study is particularly relevant to the platform research in the context of the mobile app market (e.g., Bresnahan and Greenstein 2014). Recent research from the IS, Marketing, and Economic communities has evaluated the mobile app demand in two-sided markets (e.g., Garg and Telang 2013, Ghose and Han, 2014, Lee and Raghu 2014, Yin et al. 2014, Han et al. 2016), platform choice for mobile app developers (e.g., Bresnahan et al. 2014), user engagement in mobile apps (e.g., Zhang et al. 2016, Kwon et al. 2016), product innovation and development in the mobile app market for cross promotion (Lee et al. 2014), copycat detection (Li et al. 2014), or service system innovation (Eaton et al. 2015). However, very little research has focused on the healthcare mobile app platform and the associated impact on consumer behavior. This is the main focus of our paper.

2.4 Chronic Disease and Diabetes Care

Finally, our work is related to prior studies on chronic-disease management, especially diabetes care. There have been a tremendous amount of studies on diabetes care, mainly from the medical community (e.g., Mohammed et al. 2013). The development of medical treatment is beyond the scope of this paper. However, our study builds on this prior literature, and in particular, we focus on the design and impact of personalized diabetes care and patient self-management enabled through the mHealth app platform. According to a recent study at *Cell*, researchers continuously monitored week-long glucose levels in an 800-person cohort, measured responses to 46,898 meals, and found high variability in the response to identical meals, suggesting universal dietary recommendations may have limited utility and that personalized diets may successfully modify elevated postprandial blood glucose and its metabolic consequences (Zeevi et al. 2015). The mHealth app platform offers a unique, personalized channel for patient self-management.

3. A Randomized mHealth Field Experiment

To evaluate the effectiveness of the mHealth app on patients' behavior and health outcomes, one could collect secondary app user data and examine the user health behavior before and after the app adoption. However, the critical challenge for such an archival data analytical approach is the potential (strong) self-selection bias in the app user population. For example, users who care more about their health will be more likely to adopt the mHealth app, and will be more likely to change their behavior and life style in a healthier direction. This self-selection could lead to a statistically significant and positive correlation between the app adoption/usage and user health over time. However, this positive relationship might be endogenous, because of the potential unobserved user-level attributes that lead to the app adoption/usage in the first place. Therefore, ideally we would like the users to be randomly assigned to use the mHealth app—those who use the app and those who do not use the app will show no significant difference statistically. If so, the difference in their health behavior change before and after the app adoption would be attributed solely to the impact of the app adoption/usage over time. Unfortunately, using only secondary data, we cannot easily identify such an impact from a causal perspective.

Therefore, to ensure the random assignment of users, we propose to design and implement a randomized field experiment by partnering with a major mHealth company in Asia that provides the largest mHealth app platform in the nation that specializes in diabetes care. In this section, we will first introduce the background of this mHealth app platform. Then, we will discuss in detail how we design and implement our experiment.

3.1 Mobile Health Platform Background

Our research partner is a major mHealth firm in Asia. It provides the largest mHealth platform for chronic-disease management, specializing in diabetes care. To date, the mobile platform has 156,120 active registered users and 9,970 affiliated physicians who specialize in diabetes care across the nation. In addition to the external expert network, the platform also has a full-time internal expert team with more than 20 medical professionals including physicians, pharmacists, nurses, psychologists, and nutritionists. The platform integrates all these medical resources into a mobile app for patients.

This patient app provides diabetes patients with 24/7 services with four sets of core functions to facilitate patient self-management: (1) Behavior Tracking: patients can record and upload at any time their blood glucose, blood pressure, exercises, diet, weight, sleep, and so on. (2) Risk Assessment and Personalized Solutions: a cloud-based backend data analytic system will analyze individual patients' data and assesses the real-time health risk for each patient by taking into consideration 45 different types of medical conditions, including the stage and type of diabetes, whether the patient is pregnant, whether the patient has a complication, and so on. Based on the data analytic results, the app will recommend personalized self-management solutions for each patient regarding diet, exercise, life style, and potential medication. To ensure the validity of the recommendation, the internal medical team will view and discuss the data analytic results and personalized solutions regularly to improve the algorithm. (3) Q&A: the patients can contact the physicians in the internal and external expert networks for free consultation at any time regarding the medication, treatment, or self-management of their health. (4) Patient Community: the patients can participate in a digital community through the mobile app platform to discuss and communicate with each other.[9]

For a better understanding of the patient app function, we provide screenshots of the major functions in Figure 1. In particular, (1a) illustrates the overview of the user homepage after login. Figure (1b) illustrates the page of recording a new blood glucose value. Figure (1c) illustrates a set of user behavior tracking pages that visualize blood glucose, blood pressure, diet, and exercise over time. In addition, we also provide more screenshots for other related app functions in Figures A2 and A3 in Appendix A.

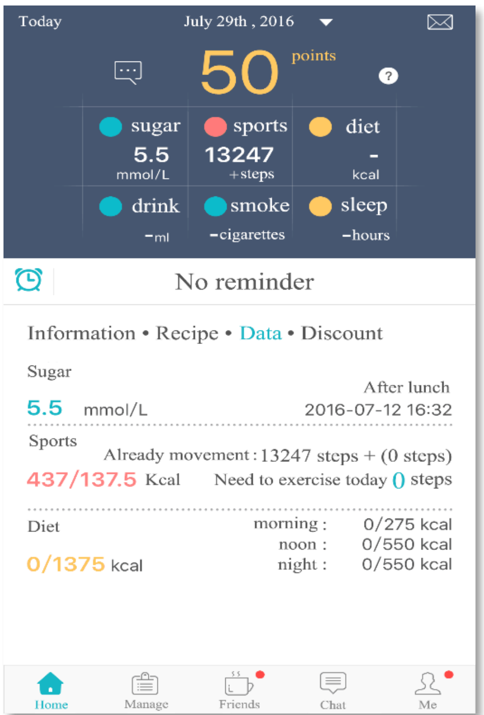
One critical challenge from the app platform designer's perspective is to examine how effective the app is in actually improving the patient health behavior and outcomes over time. To achieve this goal, we designed a large-scale randomized field experiment, which we discuss next.

3.2 Experiment Design and Implementation

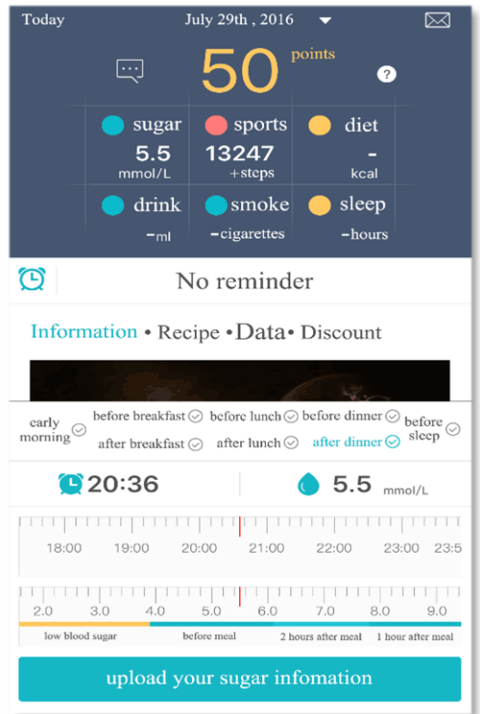
We designed and implemented a nationwide large randomized field experiment by partnering with the firm. Our national campaign for the event was successfully supported by the Office of Chronic Disease Management from the Ministry of Health and received widespread attention from the society. To examine the impact of the mHealth platform under various situations, we designed five experimental conditions (2 Control groups + 3 Treatment groups) as follows:

- Control Group (C1): No treatment, behave as usual;
- Control Group (C2): Use the web (PC) version of the health app;
- Treatment Group (T1): Use the mHealth app;
- Treatment Group (T2): Use the mHealth app + Receive non-personalized SMS reminder messages with general knowledge about diabetes care twice a week; and
- Treatment Group (T3): Use the mHealth app + Receive personalized SMS reminder messages with patient-specific health advice from the internal expert team twice a week.

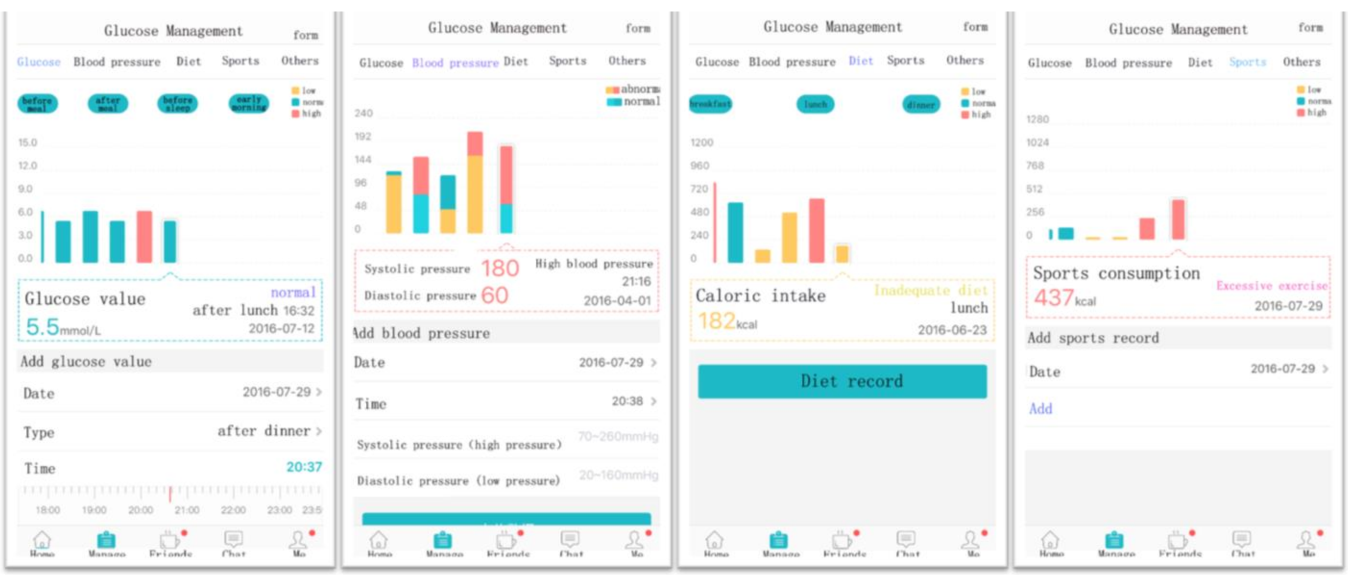
[9] Aside from the patient app, this company also provides a physician app whereby affiliated physicians can build their own "digital clinics." In this paper, we will not focus on the physician app. We leave this topic to interested researchers for future work.



(1a) Overview of User Homepage



(1b) Adding a New Blood Glucose Value



(1c) User Behavior Tracking over Time.
(from left to right: Glucose, Blood pressure, Diet, and Exercise (Sports))

Figure 1. Screenshots of the Main App Functions

Control group C1 is the baseline. Control group C2 is a second baseline to examine the potential device effect that can lead to differences in the effectiveness of the diabetes self-management application.

Treatment group T1 contains the normal mHealth app users who have access to all four sets of app functions. We designed treatment group T2 to test the potential synergetic effect when the mHealth app is paired with the mobile SMS messaging; research has shown the latter alone to be effective in improving patient treatment adherence and health outcomes (e.g., Lester et al. 2010). Finally, we designed treatment group T3 to further test the potential impact from the design of the SMS messaging, which were shown to have a significant influence on the effectiveness of the mHealth interventions (Pop-Eleches et al. 2011, Free et al. 2013). We provide an example of the two types of mobile SMS messages in Figure A4 in Appendix A.

We recruited participants for our experiment based on a voluntary basis through a combination of channels, including announcements through several national major news websites, social media and social networks via both web and mobile platforms, as well as offline recruiting through local hospitals and communities. Upon registration, each participant was randomly assigned to one of the five experimental groups. As compensation for their time and efforts, participants were automatically enrolled in a lottery upon completion of the experiment. The potential rewards from the lottery included Apple Watch, Fitbit smart bands, blood glucose meters, air purifiers, or gift cards with various values (from $5 to $750).

The initial round of participant recruitment started in May 2015. One practical challenge in medical trials is the potential delays in recruitment and the high rates of dropout, which might lead to uncertainty in the treatment effectiveness and might confound results (e.g., Watson and Torgerson 2006, Gupta et al. 2015). To ensure an effective sample size, we conducted the experiment by recruiting participants on a rolling "first-come-first-served" basis until the target sample size was met. Such an approach is common in medical trials (e.g., Gupta et al. 2015). Overall, the recruitment period spanned over seven months, from May 2015 to Dec 2015.

The treatment period of the experiment lasted for three months (90 days) starting from the day of registration. Based on the random assignment to the experimental group, each participant received the corresponding treatment according to the experimental design during the treatment period. In addition, to collect patient-level demographics and medical history, as well as to evaluate the potential economic impact of the mHealth platform on patients' medical costs and hospital visits, we conducted additional surveys through telephone interviews before and after the treatment period. In particular, we interviewed each participant twice—first at the beginning of the experiment (during registration) and again five months after the last day of the treatment period. Therefore, for each participant, the total experimental period lasted for eight months (i.e., pre-treatment survey + 3-month treatment period + 5-month post-treatment period + post-treatment survey). Overall, the entire experimental period for all our participants spanned 15 months from May 2015 to July 2016.[10]

During the two telephone interviews for the pre- and post-treatment surveys, we asked the participants about their demographics, medication and medical history, most recent blood glucose and glycated hemoglobin levels, frequency of hospital visits, medical costs, and so on. Informed consent was obtained at each phase of the study that required data collection. In the next section, we will discuss in more detail the exact survey variables we collected.

Note that to eliminate potential confounding factors, during the experimental period we ensured the following facts: (1) no participant had previously adopted the mHealth app prior to the registration to our experiment; (2) participants who were assigned to the two control groups did not happen to adopt the mHealth app during the experiment on their own;[11] (3) participants did not adopt other similar apps during the experiment.[12] Finally, to avoid potential bias due to misalignment with participants' prior expectation, we followed prior social and behavioral research methods (Hoyle et al. 2001) and ensured that the recruitment announcement only revealed the general purpose of the experiment (i.e., to help improve diabetes care), whereas it did not reveal the exact details of the experiment (i.e., to study the impact of adoption of mHealth app on diabetes patient behavior).

4. Data

[10] The last batch of participants was recruited in December 2015, and they completed the experiment and surveys by the end of July 2016.
[11] We validated these first two facts by crosschecking the phone numbers between the participants and the mHealth app adopters in the company database, and also through the post-treatment survey to exclude those who were not supposed to be adopters of the app prior or during the experiment.
[12] We validated this fact through the post-treatment survey to exclude the potential impact from other similar apps.

In this section, we will describe our data from both the experiment and the pre- and post-treatment surveys. We first illustrate our data sampling procedure during the recruitment and randomization processes. To validate our samples, we conducted the randomization check and briefly discuss it.

4.1 Randomization and Sampling

Our recruitment process led to the enrollment of 1,770 patients. To ensure minimum confounding factors, we excluded 427 (24.1%) patients from our sample who did not have diabetes (e.g., people whose blood glucose value was reaching the upper bound of the normal range but were not classified as diabetic yet), or had other major chronic disease(s) at the same time (e.g., kidney disease, heart disease, arthritis, HIV/AIDS), or were already users of the app. These exclusions led to a sample of 1,343 patients whom we randomly assigned into one of the five experimental groups. During the three-month treatment period, 273 (15.4%) patients dropped out.[13] Hence, our final eligible sample for analysis contains 1,070 patients, 60.5% of the original enrolled sample. We illustrate the flow of the randomization and sampling procedure in Figure 2.

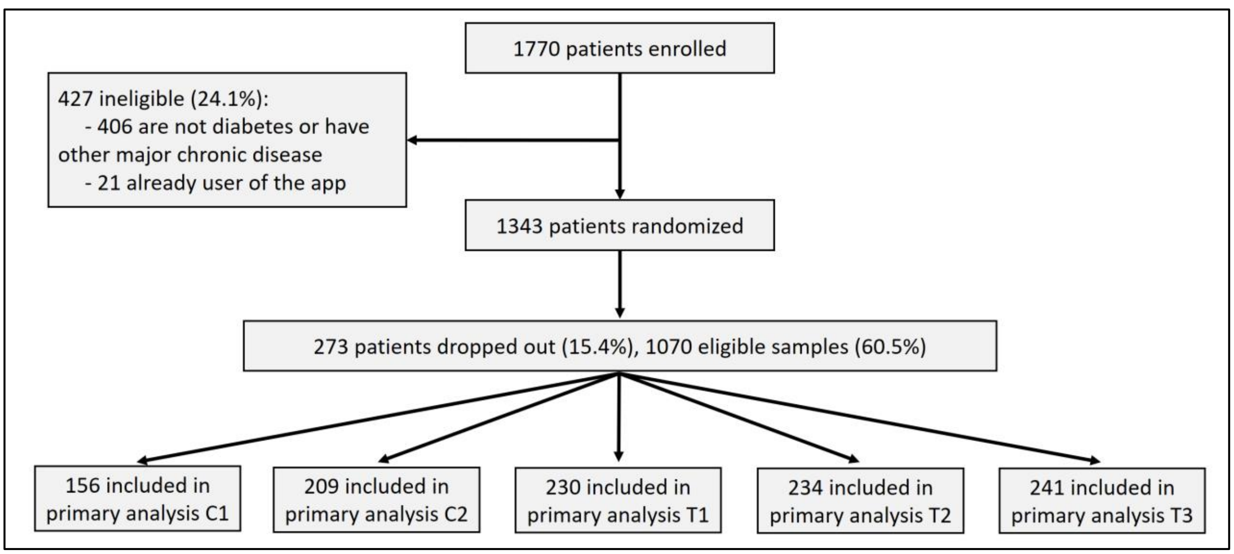


Figure 2. Randomization and Sampling Procedure

4.2 Data Description

[13] Note that high patient dropout rate is a common challenge in medical trials (e.g., Gupta et al. 2015). To alleviate any additional concern towards this issue, we compared the distributions of participants' demographic and baseline health-related characteristics between the dropout samples and the eligible samples. We did not find statistically significant difference between the two. Therefore, while we acknowledge this fact as one potential data limitation in our study, we are more confident that it is not a serious concern in affecting our results.

Our main experimental data contain a combination of two data sets: (1) Panel data of individual health and behavior characteristics recorded through the mobile (or web-based) health application during the three-month treatment period. This information includes diabetes-related health activities such as glucose value, glucose type (e.g., pre-/post-breakfast, pre-/post-lunch, pre-/post-dinner, before sleep), uploading time/date, number of communications with the medical expert team, the number of movement steps, and calories burned.[14] (2) Survey data of individual demographics, health, and behavior characteristics from the pre- and post-treatment surveys. This information contains individual age group, gender, marital status, income level, diabetes type (i.e., type 1, type 2, gestational), diabetes age (time since diabetes was first diagnosed), frequency of glucose monitoring, whether the patient has any complications, the most recent blood glucose value and type, glycated hemoglobin for the most recent three months, average time for exercise and sleep per day during the most recent three months, average calories per meal during the most recent three months, whether the patient is a smoker or drinker, whether the patient is pregnant or not, current and past medication, medical history (e.g., blood pressure, blood fat, family history), frequency of hospital visits per year, frequency of hospital visits during the last three months, and medical costs during the last three months. The survey data also contain information on individual app-related activities including registration time/date, frequency of app daily usage, and satisfaction rate. For details on these variables, we provide the summary statistics in Table 1.

To validate the randomization procedure, we conducted a randomization check. We provide the details about the randomization check in Table 2. Across the five experimental groups, we compared the distributions of the patient demographics and baseline health characteristics. We found the distributions are similar across groups. Furthermore, to better control for the potential variation in the patient-level characteristics, we included all these variables in our primary analyses as control variables. We will discuss more details in the next section.

[14] Notice that for the control group (C1) that did not use the mobile or web-based health application, we asked the participants to upload their most recent glucose values at least twice: at the beginning and end of the three-month treatment period through a web portal we designed. We provide the screenshot of this web portal in Figure A1 in Appendix A.

5. Analysis and Findings

In this section, we discuss how we analyzed the experimental data to examine the impact of the mHealth platform on patient health behavior and outcomes. Note we have both the panel data on patient health and behavior characteristics during the three-month treatment period, and the cross-sectional survey data before treatment (upon registration) and five months after treatment. We first conduct a group-level analysis using the survey data to compare the difference in patient health and behavior before and after the treatment. Then, we use the panel data to conduct the analysis of the treatment effect at the individual level.

5.1 Group-Level Analysis

First, we conduct a group-level analysis using the survey data to compare the difference in patient health and behavior before and after the treatment. Note the total time period between the two surveys is eight months: a three-month treatment period plus a five-month post-treatment period. By doing so, we aimed to capture the potential long-term effect of the treatment. In particular, across the five groups, we compare the differences in the blood glucose and glycated hemoglobin levels, the number of hospital visits during the most recent three months, and the total medical spending related to diabetes during the most recent three months. We provide the details in Table 3. The values across groups are statistically different at the $p<0.05$ level based on the one-way ANOVA test.

Table 3. Results from the Group Mean Analysis

Treatment Group	Diff-Glucose	Diff-Hemoglobin	Diff-Hospital Visits(3Mons)	Diff-Spending (3Mons, USD)
C1 (n=156)	-0.0287	-0.0143	-0.0283	-0.95
C2 (n=209)	-0.5173	-0.1967	-0.0568	-5.70
T1 (n=230)	-0.6291	-1.0316	-0.1208	-8.55
T2 (n=234)	-0.6790	-1.1612	-0.1393	-11.55
T3 (n=241)	-0.5746	-0.9405	-0.2264	-31.00

***Note*:** Values are calculated based on the difference between the two surveys (post-treatment value minus pre-treatment value). Glucose value is calculated based on an average across all glucose types. **P<0.05 (ANOVA)**

The first thing we notice is that in the baseline control group (C1), the four variables stayed relatively stable before and after the treatment, whereas all other groups that used the health application (whether mobile- or web-based) showed a significant reduction in patient glucose and hemoglobin values, as well as a reduction in hospital visits and medical spending. This finding is promising. It indicates the health platform for diabetes self-management indeed has a significant effect on improving patient health outcomes as well as reducing costs.

Second, compared to the second baseline group (C2) with web-based health intervention, the three treatment groups with mHealth interventions (T1, T2, T3) experienced a significantly higher impact on patient health and costs. For example, under the same functional setting of the health application, we observe a 21.6% increase in the mobile-based platform's (T1) impact on reducing patients' glucose, compared with the web-based platform's (C2) impact. This result is consistent with previous findings indicating a significant mobile device effect (e.g., Xu et al. 2016, Wang et al. 2016). Such an effect can become salient in the context of personal health management through faster and more flexible user response to real-time information (Ghose 2016) and mobile-enhanced user self-efficacy (e.g., Lin et al. 2016).

Third, we notice that among the three mobile treatment groups, T2, when we paired the mHealth app with simple non-personalized SMS reminder messages about general guidance on diabetes care, demonstrates the strongest treatment impact on reducing blood glucose[15] levels over time, 18.2% higher than personalized SMS message interventions with patient-specific medical guidance and 7.9% higher than no mobile message intervention at all. Interestingly, T3, when we paired the mHealth app with personalized SMS messages about patient-specific medical advice, does not perform better than T2 or T1 in helping patients improve their health outcome. This finding is surprising but highly consistent with prior research findings that the design of the SMS messaging has a significant influence on the effectiveness of the mHealth interventions (Free et al. 2013), and that more personal and encouraging words in longer text messages were not more effective than either a short reminder or no reminder, because of potential habitation or perceived intrusion (Pop-Eleches et al. 2011), and that personalization might lead to potential privacy concerns and information overload for consumers (e.g., Aral and Walker 2011, Goldfarb and Tucker 2011, Ghose et al. 2014). Moreover, our finding is also consistent with prior medical research on the impact of personalization

[15] We also see a consistent trend in the Hemoglobin value.

in healthcare effectiveness (e.g., Harle et al. 2008, Harle et al. 2012). Previous findings suggested that personalization and interactive features did not lead to increases in user attention or systematic information processing, and potential explanations are that personalized health messages that are inconsistent with patients' prior beliefs may be less persuasive and lead to information avoidance (Klein and Stefanek 2007, Harle et al. 2008).

Finally, when looking into the patient hospital visits and medical spending, we find T3 demonstrates the highest impact in reducing the two. T3 is 62.5% and 168.4% more effective compared with T2, the next best treatment, in reducing hospital visits and medical spending, respectively. This result suggests the potential of the mHealth app combined with personalized SMS messaging to reduce the medical and operational costs for diabetes patients and healthcare providers. Although personalized messaging is not more effective in affecting patient health outcome than non-personalized messaging, it might facilitate a personal connection between patients and physicians, which can lead to increased patient trust in the mHealth platform, hence reducing patients' need (or urge) to visit hospitals or take additional medication.

Note that all the analyses in this subsection are based on the cross-sectional survey data and are conducted at the group (mean) level. The impacts here should be interpreted as the group-level mean treatment effect. To further account for the potential heterogeneity within the group, we conducted individual-level analysis using the panel data set, which we will discuss in the next subsection.

5.2 Individual-Level Analysis

To better control for the potential individual heterogeneity and explain the potential discrepancy in the observed outcome, we conduct individual-level analysis using the panel data of individual health and behavior characteristics we collected during the three-month treatment period. Because our recruitment is conducted on a rolling basis, we consider the time indicator in our context as the time elapsed since the patient started the experiment. Particularly, in our primary analysis, it is defined as the unique sequence number of each patient's uploaded glucose value.

5.2.1 Time Trends

First, we would like to examine the overall time trends in each experimental group regarding the blood glucose change over time at the individual patient level. We plot the glucose value over time for each group in Figure 3.

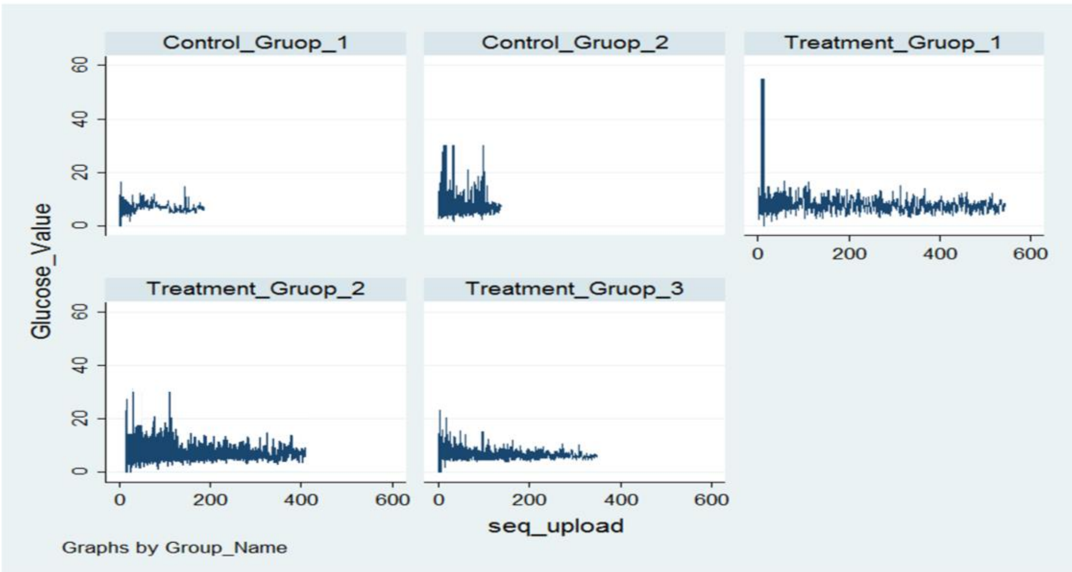


Figure 3. Comparison of Time Trends for Blood Glucose Values over Time

The Y-axis is the glucose value for each individual patient. The X-axis is the sequence number as the time indicator. We show the plots for both control groups and treatment groups at the individual level. From the time trend plots, we notice the three treatment groups on average uploaded more glucose values than the two control groups. This finding indicates a potential positive impact of mHealth in improving patient engagement with diabetes management. Furthermore, we see a noticeable downward trend over time in the three treatment groups compared to the two control groups. This finding suggests the mHealth platform seems to be able to help reduce patient glucose levels over time at the individual level. To further validate this finding, we conduct an individual-level model analysis and will discuss next. [16]

5.2.2 Diff-in-Diff Model Analysis

To account for the patient-level baseline time trend, we apply a diff-in-diff method to model individual-level glucose change over time. In particular, the first-level difference is the within-group glucose

[16] We also noticed an outlier in the T1 group at the very beginning, with a glucose value equal to 55. After consulting with the company and the internal medical experts, we decided to remove that sample from our primary model analysis.

change over time (i.e., group-specific time trend), and the second-level difference is the discrepancy in this time trend across groups. Put more formally, we model the glucose value $Glucose_{it}$ for patient *i* at time *t* as follows:

$$Glucose_{it} = \beta_0 + \beta_1 Treatment_i + \beta_2 Time_t + \beta_3 Treatment_i \times Time_t + \boldsymbol{X_i \beta_4} + \boldsymbol{C_{it} \beta_5} + \varepsilon_{it}, \quad [1]$$

where $Treatment_i$ represents the indicators of the five experimental groups. $Time_t$ represents the time indicator. $\boldsymbol{X_i}$ is a vector of control variables for patient-specific time-invariant characteristics including age group, gender, income level, marital status, diabetes type, diabetes age, frequency of glucose monitoring, whether the patient has any complications, most recent glucose and glycated hemoglobin levels prior to the experiment, average time for exercise and sleep per day and average calories per meal prior to the experiment, whether the patient is a smoker or drinker, whether the patient is pregnant, whether the patient has any other health concerns, such as high blood pressure or cholesterol, whether the patient is currently on any medications, and whether any patient-physician interaction occurred during the three-month treatment period. $\boldsymbol{C_{it}}$ is a vector of control variables for patient-specific time-varying characteristics including the time of day (morning, afternoon, evening), day of the week (Monday ~ Sunday), and month indicators of the corresponding glucose uploading activity, uploaded glucose type, daily exercise from the patient (total steps), as well as the patient's frequency of daily app usage (including all types of activities). $\varepsilon_{it} \sim i.i.d., N(0,1)$ is a stochastic error to capture any randomness in patient behavior. In the estimation, we cluster the ε_{it} at the experimental group level to account for potential within-group relationships.[17] We have tested different models (Models I ~ IV) with different combination of the set of control variables.

We provide our estimation results from these models in Table 4. In the estimation, the primary coefficient of interest is β_3, which is a vector that contains coefficients for the four interaction effects ($Treatment_i \times Time_t$). Note the control group indicator C1 is dropped due to collinearity (i.e., the interaction effect between C1 and $Time_t$ will be captured as the baseline effect, β_2, the coefficient of $Time_t$).

[17] We also tried to estimate the model without the clustered error, and found the results are highly consistent.

All four models demonstrate similar estimation results and provide evidence consistent with our previous group-level analyses. First, we notice that all four groups (C2, T1, T2, T3) experience a significant reduction in patient glucose values. This finding indicates the diabetes self-management platform (whether mobile- or web-based) is effective compared with the baseline control group (C1) that did not use the platform. Second, comparing T1 with C2, we notice a significant device effect: the mobile-based platform is more effective than the web-based platform in reducing patient glucose levels over time. Third, when comparing the three mobile-based treatment groups (T1, T2, T3), we see an interesting trend: T2 (the mHealth app with non-personalized mobile SMS reminder messages) is overall most effective in helping patients reduce their glucose over time, whereas T3 (mHealth app with personalized mobile SMS messages) is less effective than T2 or T1. This observation is consistent with our findings from the group-level analyses as well as the prior literature (e.g., Harle et al. 2008, 2012), indicating the design of the mobile SMS messaging plays an important role in the effectiveness of the mHealth interventions on patient health outcomes (e.g., Free et al. 2013, Pop-Eleches et al. 2011). Carefully designing the content, format, intensity, and delivery mode of the SMS messaging is critical. Finally, when looking at the baseline coefficients, we see the majority of the four baseline coefficients for the treatment groups (β_1) are not statistically significant. This finding further validates our random group assignment indicating the initial glucose values do not seem to vary significantly across groups. Moreover, when looking at the baseline coefficient for $Time_t$, we find β_2 is statistically significant and positive for all groups. This finding indicates the baseline time trend of patient glucose for control group (C1) without any intervention is increasing over time. This result delivers an important message. It indicates the potential risk and challenge in diabetes care over time, and suggests the importance of empowering patients to improve their self-management for diabetes through smart and digital health platforms.

5.3 Patient-Level Fixed Effect

In the previous section, we considered a large number of patient-level characteristics in the individual-level analysis to control for individual-level heterogeneity. To further account for any other potential unobserved individual characteristics, we conduct the diff-in-diff analysis with patient-level fixed effects as follows:

$$Glucose_{it} = \beta_0 + \beta_1 Time_t + \beta_2 Treatment_i \times Time_t + \mu_i + \boldsymbol{C_{it}\beta_3} + \varepsilon_{it}, \qquad [2]$$

where μ_i captures the patient-level fixed effect. Note that in this model, we drop the treatment group indicator $Treatment_i$ and the patient-specific time-invariant characteristics $\boldsymbol{X_i}$ from the model because of collinearity with the patient fixed effect. The primary coefficient of interest is $\boldsymbol{\beta_2}$, the interaction between the treatment group indicator and time. We estimate the model with the patient-specific time-variant characteristics, $\boldsymbol{C_{it}}$ (Model V), and without, $\boldsymbol{C_{it}}$ (Model VI). The corresponding estimation results are shown in Table 5.

Overall, our findings from the patient-level fixed-effects model demonstrate high consistency with our previous analysis using the treatment-group-level fixed effect (i.e., equation [1]). We find the adoption of the mobile-based platform (T1, T2, T3) can significantly improve the health outcome of diabetes patients in reducing their blood glucose values over time, even after controlling for the individual-level fixed effects. Moreover, we also see a consistent trend: in conjunction with the mHealth app platform, non-personalized mobile messages with general guidance for diabetes care have a higher impact on patient health improvement than personalized mobile messages. These additional empirical analyses provide us with robust evidence and strong confidence in our results.

5.4 Summary of Main Findings

Overall, our group-level analyses and individual-level analyses demonstrate highly consistent evidence that mobile health app platforms have a significant impact on empowering patients with diabetes self-management, reducing patients' glucose values and improving their health outcomes over time.

More specifically, first, we find the adoption of the mHealth platform indeed has a significant impact on improving diabetes patient health outcomes as well as reducing medical costs. This insight is the most critical one from this research, demonstrating the great potential of mHealth in empowering diabetes patients for efficient and effective health management. Second, between web-based and mobile-based platforms, we find a strong device effect: the mobile interventions led to a significantly higher impact than the web-based intervention. Third, in conjunction with patient self-management through the mHealth platform, we also find heterogeneous effects between personalized and non-personalized messages. We notice that pairing the mHealth app with non-personalized SMS reminder messages about general diabetes care led to the largest average health impact on reducing patient glucose levels. Nevertheless, pairing mHealth app with personalized SMS messaging of patient-specific medical advice did not seem to be more effective than non-personalized reminder messaging or no messaging in reducing blood glucose values. However, personalized SMS messaging is most effective in reducing patients' hospital visits and medical costs. Our findings provide insights on mobile health platform design. They are in line with prior research from the medical community suggesting the importance of the design for mobile SMS messaging when paired with the mHealth app platform to improve the impact of mHealth on patient empowerment. Understanding patient behavior and interaction with the platform, and incorporating this knowledge into designing more effective mHealth applications and platforms for patient engagement and empowerment, is important.

6. Conclusion and Future Directions

In this paper, we have examined the emerging mHealth platform and its health and economic impacts on diabetes patient outcomes. To achieve our goal, we partnered with a real-world testbed in Asia that provides the nation's largest mobile health app platform that specializes in diabetes care, together with the Office of Chronic Disease Management from the national Ministry of Health. We have designed and implemented a large-scale randomized field experiment based on 9,251 unique responses from 1,070 diabetes patients over a 15-month period from May 2015 to July 2016. Our research demonstrates the adoption of the mHealth platform has a statistically significant impact on reducing patients' blood glucose and glycated hemoglobin levels, hospital visits, and medical expenses over time. Moreover, in conjunction with patient self-management through the mHealth platform, we also find heterogeneous effects between personalized and non-personalized messages. Interestingly, non-personalized mobile messages with general diabetes-care guidance demonstrate a stronger impact on patient health improvement. Our study indicates the mHealth platform can have great potential for improving patients' health outcomes, by assisting them with behavior modification and disease self-management. It also provides important insights into the design of the mHealth platform to achieve greater medical and economic outcomes.

On a broader note, our research will significantly improve our understanding of human behavior and interactions with smart and connected mHealth platforms, and broadly in the consumer Internet of Things (IOT). Digital health platform infrastructures are often the manifestation of complex technological and social systems (Eisenmann et al. 2011) and can have profound implications on social and economic transactions. However, how humans interact with the mHealth infrastructures is not as well understood. Our study can provide important managerial insights on issues that may influence individuals' sustained engagement with mobile and wearable technology development, health and wellness, adherence to treatment and wellness regimens, the efficiency of healthcare delivery, and patient welfare. It will also improve our understanding of the key mechanisms that drive individual health and wellness behaviors and lifestyle changes through mobile and sensor technologies. Finally, it can provide critical policy implications regarding the design of smart digital health platforms through effective, sustained usage of these emerging technologies.

Our paper has some limitations, which can serve as fruitful areas for future research. First, in our data sample, the majority of the diabetes patients have type 2 diabetes (approximately 98%). Although type 2 diabetes accounts for approximately 90% to 95% of all diagnosed cases of diabetes,[18] an examination of the mHealth impact on other types of diabetes with a larger sample in future would be useful. For example, given that the regular medication and insulin use could be a serious challenge for type 1 diabetes patients, an examination of how mHealth can improve self-management and empowerment for such patients would be useful. Second, in this current study, we have evaluated the mHealth app as a bundle of all the major functions. However, breaking down the overall application into different functional components (e.g., Behavior Tracking, Risk Assessment and Personalized Solution, Q&A, and Patient Community) and examining the health and economic impacts from each of them separately would be interesting. Third, in this paper, we have not considered the potential impact related to the textual content of patient-physician

[18] http://www.healthline.com/health/type-2-diabetes/statistics

communications, mainly because of potential privacy concerns blocking access to the textual content of the personal communications. However, based on our conversation with the testbed, we believe these patient-physician communications are highly professional and provide similar quality in medical guidance. In addition, in our analyses, we are able to control the frequency of the patient-physician communications during the treatment period. Finally, our research focuses on the context of diabetes-care management. The methodologies and insights have the potential to be generalized to other chronic-disease and wellness-care contexts. However, examining other medical scenarios to compare the relationship and heterogeneity in the impact of the mHealth platform on patient behavior and outcomes under different healthcare contexts would be interesting and important for future research.

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Table 1. Summary Statistics of Main Variables

Variable	Description	Mean	Std.	Min	Max
C1	Dummy for control group 1	0.15	0.33	0	1
C2	Dummy for control group 2 (Web)	0.20	0.40	0	1
T1	Dummy for treatment group 1	0.21	0.42	0	1
T2	Dummy for treatment group 2	0.22	0.43	0	1
T3	Dummy for treatment group 3	0.22	0.43	0	1
Male	Whether the patient is male	0.65	0.47	0	1
Age	Numerical value of age	55.17	8.91	23	72
Age_30	Dummy for age group <30	0.24	0.43	0	1
Age_30_40	Dummy for age group 31-40	0.30	0.46	0	1
Age_41_60	Dummy for age group 41-60	0.39	0.49	0	1
Age_60	Dummy for age group >60	0.06	0.24	0	1
Married	Whether the patient is married	0.83	0.39	0	1
Income	Numerical value of income ($, annual)	76827.27	12258.67	29630	234524
Income_50K	Dummy for income < 50K	0.24	0.43	0	1
Income_50_100K	Dummy for income 50-100K	0.66	0.49	0	1
Income_100_200K	Dummy for income 100,001-200K	0.09	0.29	0	1
Income_200K	Dummy for income >200K	0.01	0.11	0	1
Uploaded Glucose	Patient self-uploaded real-time glucose (overall)	7.18	2.07	3.1	34.3
(Pre-meal)	Patient self-uploaded real-time glucose (pre-meal)	6.47	1.70	3.1	29.1
(Post-meal)	Patient self-uploaded real-time glucose (post-meal)	8.17	2.18	3.9	34.3
Upload_Morning	Whether uploading time is morning	0.36	0.48	0	1
Upload_Afternoon	Whether uploading time is afternoon	0.15	0.36	0	1
Upload_Night	Whether uploading time is night	0.49	0.50	0	1
Physician Interact	Number of interactions with physicians	1.94	3.26	0	9
Hospital Visits	Number of hospital visits related to diabetes during the last 3 months	2.64	6.69	0	12
Medical Spending	Amount of medical spending related to diabetes during the last 3 months ($)	57.14	63.49	20	1587.30
Daily Steps	Number of steps walked per day	3597.82	5123.67	1021	49926
Daily Calories	Amount of calories consumed per day	1090.59	169.11	438	2647
	Patient Prior Conditions				
Pre-meal Glucose	Prior (most recent) pre-meal glucose value	7.23	1.83	3.2	18
Post-meal Glucose	Prior (most recent) post-meal glucose value	9.86	4.36	4.2	30.7
Hemoglobin	Most recent glycated hemoglobin	6.72	1.98	4.6	35
Complication	Whether there is a complication	0.19	0.39	0	1
Smoking	Whether the patient is a smoker	0.09	0.28	0	1
Drinking	Whether the patient drinks >140ml alcohol per	0.08	0.25	0	1
Pregnant	Whether the patient is pregnant	0.01	0.12	0	1
Other Major Disease	Whether the patient has other major diseases	0.01	0.11	0	1
Type 2 Diabetes	Whether the patient has Type 2 diabetes	0.98	0.12	0	1
Type 1 Diabetes	Whether the patient has Type 1 diabetes	0.01	0.11	0	1
Gestational Diabetes	Whether the patient has gestational diabetes	0.01	0.12	0	1
Diabetes Age	Year(s) since diabetes was first diagnosed	5.40	5.14	0	28

#Observations N = 9,251, #patients n=1,070. **Data Period: May 2015 – July 2016.**

Table 2. Randomization Check – Demographic and Baseline Characteristics across 5 Groups

Variable	C1 (n=156)	C2 (n=209)	T1 (n=230)	T2 (n=234)	T3 (n=241)
Age					
<30	23%	22%	24%	21%	24%
30-40	31%	29%	26%	23%	21%
41-60	40%	42%	45%	51%	48%
>60	6%	6%	5%	5%	6%
Gender					
Male	65%	64%	65%	67%	66%
Female	35%	36%	34%	34%	35%
Married	82%	77%	90%	90%	86%
Income ($, annual)					
<50K	26%	25%	27%	24%	27%
50-100K	66%	65%	62%	65%	64%
100,001-200K	7%	8%	10%	10%	8%
>200K	1%	1%	1%	1%	1%
Baseline Condition					
Pre-meal Glucose	7.11	7.04	6.90	7.13	6.95
Post-meal Glucose	8.43	8.59	8.44	8.38	8.68
Glycated Hemoglobin	7.03	6.98	6.60	6.67	6.82
Complication	19%	21%	16%	18%	15%
Smoking	8%	9%	10%	9%	9%
Type 2 Diabetes	98%	96%	97%	96%	96%
Type 1 Diabetes	1%	2%	2%	2%	2%
Gestational Diabetes	1%	1%	2%	2%	2%

Note: Data are in percentage or mean value. Percentages do not add up to 100% in some cases because of rounding. The majority of our patient samples belong to type 2 diabetes, which is the main focus of our study. Income is adjusted based on the local cost of living.

To better control for the potential variation in the patient-level characteristics, we also included all these variables in our primary analyses as control variables.

Table 4. Estimation Results from the Primary Diff-in-Diff Models

Variables	Coef. (Std. Err.)[I]	Coef. (Std. Err.)[II]	Coef. (Std. Err.)[III]	Coef. (Std. Err.)[IV]
Interaction Effect ($\boldsymbol{\beta_3}$)				
$\boldsymbol{C2 \times Time_t}$	-0.3448** (0.1804)	-0.4606***(0.1805)	-0.4105** (0.1819)	-0.5106** (0.2059)
$\boldsymbol{T1 \times Time_t}$	-0.4107***(0.1553)	-0.4871***(0.1588)	-0.4642***(0.1589)	-0.5733***(0.1832)
$\boldsymbol{T2 \times Time_t}$	-0.4589***(0.1551)	-0.5327***(0.1565)	-0.4588***(0.1587)	-0.6170***(0.1816)
$\boldsymbol{T3 \times Time_t}$	-0.3753** (0.1506)	-0.4669***(0.1520)	-0.4243** (0.1531)	-0.5408** (0.1802)
$C2$ (β_1)	1.4013 (1.5766)	3.2889 (2.6396)	1.5622 (0.9973)	4.7363 (3.4386)
$T1$ (β_1)	0.8605 (0.6704)	0.8829 (0.6837)	0.8565 (0.6912)	1.1794 (1.0350)
$T2$ (β_1)	0.8282 (0.6747)	0.9042 (0.6893)	0.9756 (0.6919)	1.1432* (0.6361)
$T3$ (β_1)	0.9583 (0.6784)	0.9424 (0.6893)	1.0193 (0.6893)	1.2649* (0.6347)
$Time_t$ (β_2)	0.3095** (0.1528)	0.3920***(0.1545)	0.3674** (0.1559)	0.4755***(0.1822)
$Intercept$ (β_0)	13.3714***(0.9649)	11.4988***(1.0279)	11.8268***(0.8336)	10.5798***(1.8447)
Patient-Specific Control Variables ($\boldsymbol{X_i}$)				
Age, Married, Gender, Income, Prior Glucose, Prior Hemoglobin, Prior Medication, Other Disease, Complication, Smoking/Drinking, Pregnant, Diabetes Type, Interaction with Physicians.	Yes	Yes		
Patient-Time-Specific Control Variables ($\boldsymbol{C_{it}}$)				
Diabetes Age, Uploaded Glucose Type, Upload Time/Day/Month, Daily Exercise (#Steps), Daily App Usage.	Yes		Yes	

Note: * p<0.1, ** p<0.05, *** p<0.01. Errors are clustered at the experimental group level. Age and Income are in log form. Models I~ IV include different sets of control variables. #patients=1,070, #observations=9,251.

Table 5. Estimation Results from the Diff-in-Diff Model with Patient-Level Fixed Effects

Variables	Coef. (Std. Err.)[V]	Coef. (Std. Err.)[VI]
Interaction Effect ($\boldsymbol{\beta_2}$)		
$\boldsymbol{C2 \times Time_t}$	-0.3327** (0.1704)	-0.4267** (0.1977)
$\boldsymbol{T1 \times Time_t}$	-0.3461** (0.1795)	-0.4349** (0.1945)
$\boldsymbol{T2 \times Time_t}$	-0.4909***(0.1752)	-0.5172***(0.1703)
$\boldsymbol{T3 \times Time_t}$	-0.4430** (0.1951)	-0.4873** (0.1944)
$Time_t$ (β_1)	0.3557** (0.1732)	0.3936** (0.1572)
$Intercept$ (β_0)	10.1937***(1.7438)	7.3579***(1.1258)
Patient-Time-Specific Control Variables ($\boldsymbol{C_{it}}$)		
Diabetes Age, Uploaded Glucose Type, Upload Time/Day/Month, Daily Exercise (#Steps), Daily App Usage.	Yes	

Note: * p<0.1, ** p<0.05, *** p<0.01. Errors are clustered at experimental group level. Age and Income are in log form. Models I~ IV include different sets of control variables. #patients=1,070, #observations=9,251.

Appendix A. Screenshots of Mobile/Web Interfaces

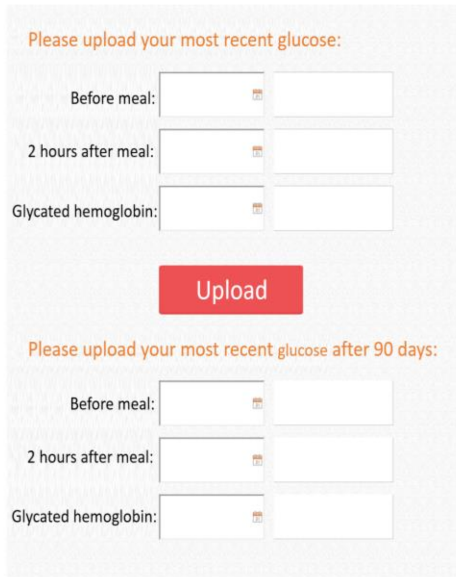

Figure A1. Screenshot of the Web Portal for Control Group C1 to Upload the Blood Glucose and Hemoglobin Values at the Beginning and End of the 3-month Treatment Period

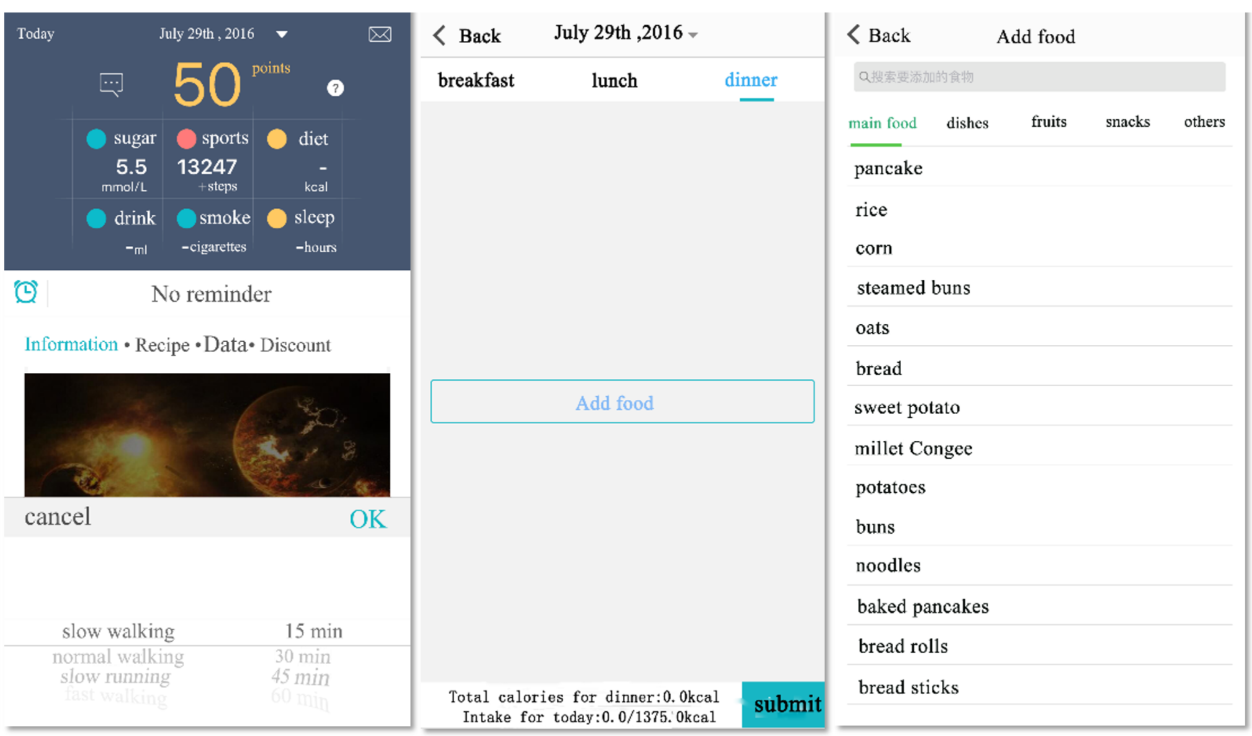

Figure A2. Screenshots of the Behavior Recording Pages (Exercise and Diet)

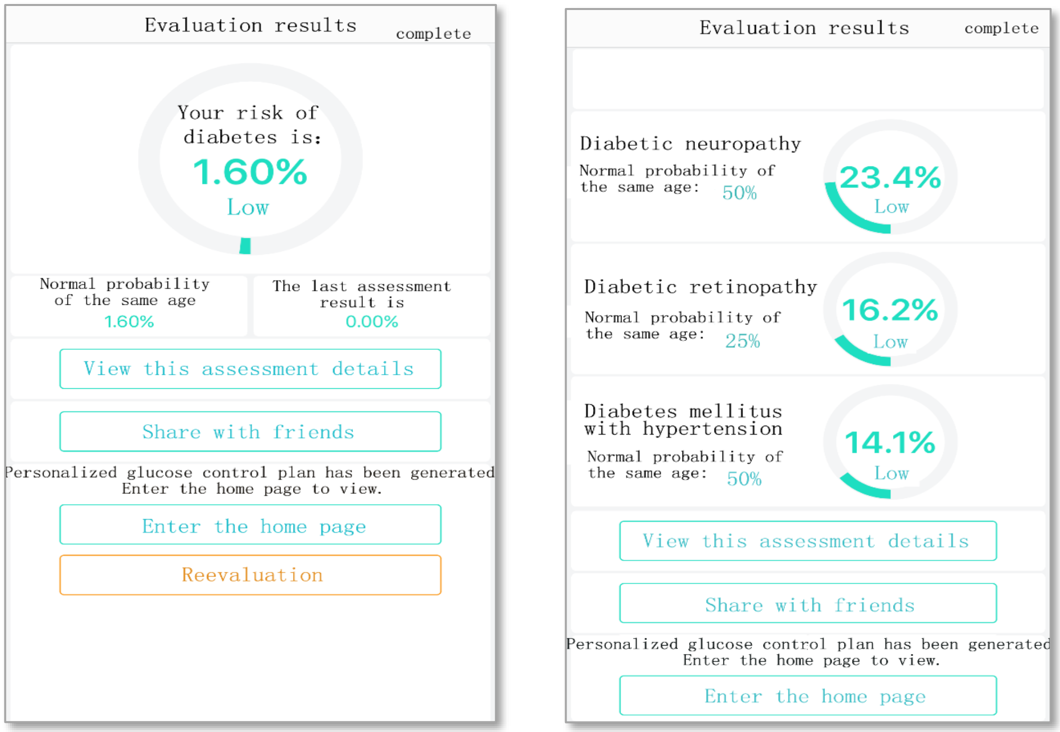

Figure A3. Screenshots of the Diabetes Risk Assessment Pages

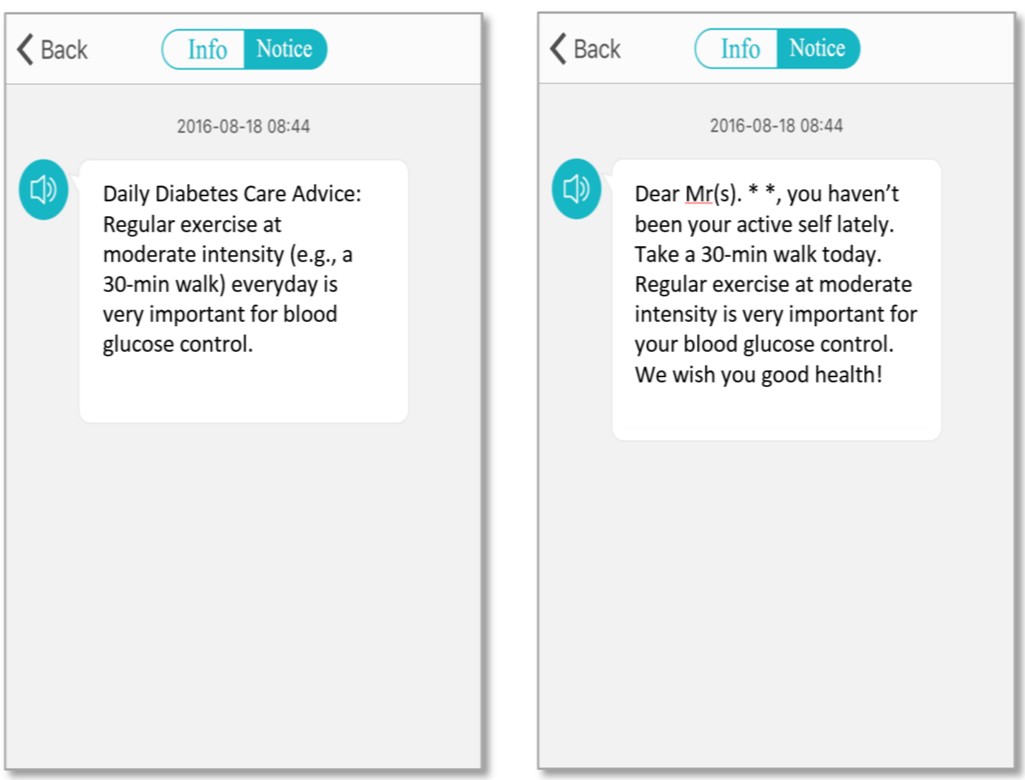

Figure A4. Screenshots of the Mobile Messages (Left: Non-personalized; Right: Personalized)