MEDINFO 2015: eHealth-enabled Health
I.N. Sarkar et al. (Eds.)

doi:10.3233/978-1-61499-564-7-89

Mobile App to Reduce Inactivity in Sedentary Overweight Women

Joseph Finkelstein, McKenzie Bedra, Xuan Li, Jeffrey Wood, Pamela Ouyang

Johns Hopkins University School of Medicine, Baltimore, MD, USA

Abstract

Recent studies demonstrated that the duration of inactivity (sedentary state) is independently associated with increased risk of cardiovascular disease. Our goal was to develop the technology that can measure the amount of inactivity in real time, remind a person that a preprogrammed period of inactivity has occurred and encourage a period of activity, and provide web-based feedback with tailored information to the participant and investigators. Once it was developed, we carried out a pilot study in a group of sedentary overweight women. The objective of the study was to assess potential of the mobile app to reduce inactivity in our target population. A randomized crossover design was employed with study subjects randomly assigned to a 4-week each "message-on" and "message-off" periods. Out of 30 enrolled subjects, 27 completed the study. The average age of particpants was 52±12; BMI: 37±6; 47% were white and 47% were African American. Overall, inactivity was significantly lower (p<0.02) during "message-on" periods (24.6%) as compared to the "message-off" periods (30.4%). We conluded that mobile app monitoring inactivity and providing a real-time notification when inactivity period exceeds healthy limits was able to significantly reduce inactivity periods in overweight sedentary women.

Keywords:

Inactivity, mobile app, eHealth, telemonitoring

Introduction

Cardiovascular disease (CVD) is the leading cause of death in women in the USA. The risk factors contributing to CVD include obesity (strongly associated with insulin resistance), diabetes, inflammation, and dyslipidemia. Prevalence of CVD is lower in women than in men; however, women with diabetes carry a higher risk for CVD. Studies suggest that women with diabetes mellitus (DM) without known CVD have a greater mortality than women without DM but with known CVD.[1] Exercise reduces obesity and visceral adiposity, increases peripheral muscle glucose utilization, and increases insulin sensitivity.

The US federal guidelines recommend a daily moderate-intensity physical activity for 30 minutes. Despite these recommendations, the prevalence of obesity and diabetes continues to increase, and it is predicted that US obesity may reach 42% by 2030. In addition to the well established link between physical activity and lower CVD risk, it is now becoming evident that the duration of inactivity (sedentary state) is also associated with increased risk. The risk associated with being sedentary is independent of the amount of physical activity; i.e., the effects of too much sitting rather than too little exercise also impact CV risk.[2] Studies have generally shown that people admitting to a higher number of hours of sitting have greater risk for developing diabetes, cardiovascular disease, and all-cause mortality.[3] Thus it is plausible that reducing the amount of sedentary time may reduce CVD and diabetes risk. Furthermore, the data suggest that even active individuals would benefit from reducing their hours of inactivity. This may be particularly important in women who have greater barriers to exercise.[4]

Our goal was to develop the technology that can measure the amount of inactivity in real time, remind a person that a preprogrammed period of inactivity has occurred encourage a period of activity, and provide a web-based feedback with information tailored to the participant and investigators. Once it was developed we carried out a pilot study in a group of sedentary overweight women. The objective of the study was to assess potential of the mobile app to reduce inactivity in our target population.

Materials and Methods

For inactivity monitoring we employed a physical activity tracking device (Fitbit) and an Android smartphone with digital data plan. Fitbit uses a three-dimensional accelerometer to monitor physical activity including number of steps. Fitbit is a miniature wearable device which communicates with a smartphone via Bluetooth connection to transmit the physical activity data. The physical activity data are then relayed by a smartphone to a Fitbit database hosted by the company, which provides developers with API to access the user data by custom applications.

System Design

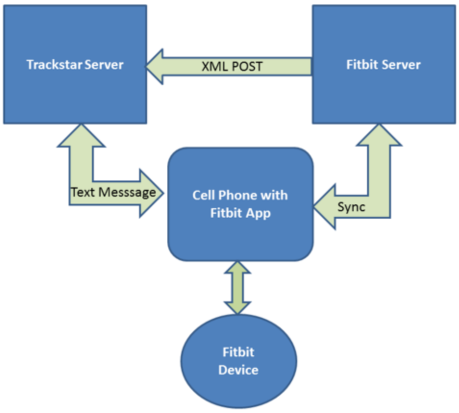

Figure 1 – Mobile App Design

The inactivity monitoring system consists of two separate programs hosted on the same server – a step monitoring app that collects data from the Fitbit users and stores it in our database, and another monitoring program that generates tailored text messages in certain situations. Both programs were developed in C# using the Fitbit API.

The step monitoring website receives POSTed XML updates from the Fitbit server whenever the Fitbit device syncs. Each Fitbit account has a subscription service activated that tells it where to POST the XML file. The XML file is sent to our site by Fitbit automatically for each registered user account. The Fitbit device syncs every 10-15 minutes when it is in the range, which defines the maximal frequency of updates received by our server in real time. Each post provides an update on the number of steps made by a particular user in an incremental manner. The step counts starts from zero every day at 00:00am.

When the site receives the XML file it records the time and number of steps which are queried for the user using the Fitbit API. It then checks to see if there have been less than 15 steps in the past hour. If there were, and no blackout conditions apply, it will send a tailored text message to the user's phone informing that sedentary period exceeded healthy limits, and encourages the user to take a break from the sedentary position. The tailored message provides suggestions from the message library on ways to have short physical activity breaks in an office environment or at home, depending on the time of the day.

The monitoring program has four different execution modes depending on the argument(s) passed. One of those modes is the sync monitor. The sync monitoring program goes through all users and checks their last sent record, which is the last time they synced. If they have not synced for an hour or more, it should send them a text message saying so, unless such a message was sent in the past hour. This mode runs every 15 minutes. This mode addresses instances when connection between Fitbit and the cell phone is lost.

The second mode is the exercise link program, which sends a link to relevant exercise education materials from the database to every user in the database every time it is run. It should cycle through all the links in the table in order and goes back to the first one after it gets to the end. The current link is stored in the database. This program is scheduled to run at 8am every Saturday and Sunday. This mode promotes user engagement in healthy lifestyle activities by empowering the user with helpful information during weekends when users have more time to review educational messages.

The third mode is the daily report program, which sends a summary of the user's steps from the previous day. It uses the Fitbit API to query a user's total steps from the previous day. This mode provides useful feedback on a daily basis helping users monitor their activity level and adjust it when necessary.

The final mode is the no sync text. This program checks whether or not a user has synced in the last 24 hours. If not, the user is sent a text message telling them this and encouraging them to reestablish connection. This mode allows to identify potential technical issues in a timely manner.

There are blackout conditions for which no messages are sent to the patient. The first blackout condition is if the user has texted "S[X]", – where X is the number after S – so that the mobile app stops sending text messages for the next X hours. If the user texts "Okay", it does not send texts for the next 1 hour. They also do not receive texts if there are blackout times corresponding to the current time set in the database for that day. Blackout hours were entered for each patient at enrollment based on their personal preferences. This mode addresses specific user preferences in terms of their schedule when they cannot use the phone.

The design of the system has been informed by two focus groups conducted in overweight sedentary women at the beginning of the development process. The app specifications tailored participants' suggestions voiced in the focus groups.

Figure 2 – Text Messaging Algorithm

Evaluation Design

A randomized crossover design was used to evaluate potential impact of the mobile app on the inactivity level (Figure 3). For this pilot we enrolled overweight sedentary women who met the following criteria.
Inclusion criteria:

- Adult women with BMI > 30 kg/m^2 who are inactive for > 3 hours on an average day

Exclusion criteria:

- Pregnant per participant's information
- Inability to walk
- Medical reasons to limit activity; e.g., unstable cardiac conditions such as angina or heart failure
- Poorly controlled hypertension, SBP >160 mm Hg, DBP >100 mg Hg (whether or not they are on antihypertensive agents)

No clinical care was provided by the research team. Participants were recruited by flyers and from previously conducted focus groups that were designed to provide feedback on the devices and messages that were used in the study. Almost all the focus group participants expressed interest in being in the study.

During the first visit the participants had their weight, height, and BP measured and blood drawn for fasting glucose and insulin. A questionnaire was administered to capture demographic and major clinical conditions to ensure that activity is possible and advisable using the American Association of Sports Medicine criteria.[5,6] Participants also completed a number of questionnaires that capture their level of activity/inactivity at work and during leisure time, as well as their readiness toward starting to increase activity. All study subjects received a Fitbit One and a smartphone. They were instructed on the use of these devices. Digital data plan and phone service were provided with the smartphone for all participants for the duration of the study. During the first 2 days (Day -2 to Day 0) participants were asked to use the devices and become comfortable with them and they were encouraged to contact the coordinator if they had any questions. The first 2 days were a regular work days and formed a baseline period of activity and inactivity. Participants were randomized to one of the two groups (Group A or B). Group A participants had the inactivity reminder system activated for time period 1 (4 weeks duration), and that function was inactivated for the second 4 weeks of the study. Group B had the inactivity reminder system inactivated for the first 4 weeks, and activated for the second 4 weeks of the

Table1 – Inactivity analysis: inactivity is expressed as fraction of the day from 8:00 am to midnight

	Inactivity of Message-off period				Inactivity of Message-on period				P-value
	Mean	SD	Min	Max	Mean	SD	Min	Max	
Total (N=27)	0.3044	0.1853	0.1200	0.9000	0.2456	0.1394	0.0700	0.6400	0.0207*
Group A (N=15)	0.3213	0.2274	0.1200	0.9000	0.2153	0.1366	0.0700	0.5200	0.0037*
Group B (N=12)	0.2833	0.1204	0.1500	0.5600	0.2833	0.1393	0.1500	0.6400	0.9824

Table2 – Analysis by steps from 00:00 am to midnight

	Steps of Message-off period				Steps of Message-on period				P-value
	Mean	SD	Min	Max	Mean	SD	Min	Max	
Total	5977.03	2108.79	2490.6	11109.9	5684.37	2148.4	2537.85	12402.61	0.5902
Group A	5614.77	1855.12	2620.55	9655	6199.11	2062.1	2969.21	9386.21	0.3303
Group B	5771.37	2552.4	2537.85	12402.6	5699.43	2224.36	2490.6	11109.89	0.8501

study. At the end of the study (Day 56), the biometric measurements and questionnaires were repeated.

In addtion to tailored text messages generated by the mobile app, the participants were allowed to see all the measurements of activity that are routinely captured and displayed by the commercial Fitbit website. This includes the number of steps per day, the number of steps climbed, distance walked, and calories burned.

At the end of the study, participants were asked their views on the devices, messages, and the effect of these on their perceptions or knowledge about activity and inactivity, the impact of these technologies on their readiness to be active, and their thoughts on whether they would be willing to continue using these devices/software for longer durations. This information will be used to improve mobile app design for a larger study.

The primary outcome of interest was the number of episodes of prolonged inactivity (> 2 hours duration) per day during the time period that the inactivity reminder was active compared to not active (time Period 1 vs 2).

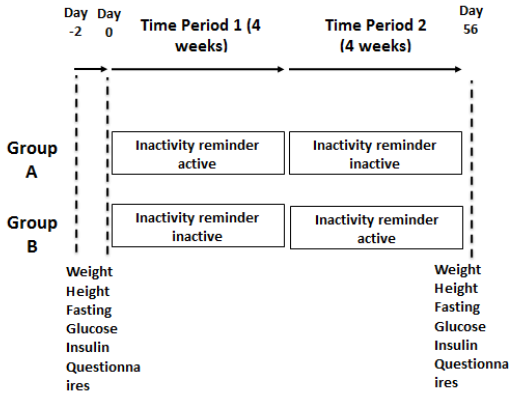

Figure 3 –Study duration and number of study visits required of research participants.

Results

Overall results were positive. Out of 30 enrolled subjects, 27 completed the study. The average age of particpants was 52±12, with average BMI of 37±6.; 47% of the participants were white and 47% were African American. There was no significant difference in baseline characteristics between Group A and B.

The inactivity was calculated as percent of consecutive 2-hour slots between 8am and midnight (total of 8 2-hr slots per day) during which the number of steps did not exceed 20 (Table 1). Overall, inactivity was significantly lower ($p<0.02$) during “message-on” periods (24.6%) as compared to the “message-off” periods (30.4%). For Group A, the mean period of inactivity as a percentage was 21.5% during the “message-on” period, and during the “message-off” period inactivity increased to 32.1% ($p<0.004$), indicating a decrease in inactivity when receiving text messages from the system. Group B, which received no tailored messaging during the first 4 weeks, showed no change when it was switched to messaging in the subsequent 4 weeks, with a mean inactivity period of 28.3% for both the “message-on” and “message-off” periods.

An analysis of the step count revealed that Group A had a higher average daily number of steps during “message-on” period (6199.1±2062.1) as compared to the “message-off” period (5614.8±1855.1). A similar but less pronounced tendency was documented in Group B with mean number of daily steps going from 5771.4±2552.4 during “message-off” period to 5699.4±2224.4 during “message-on” period.

After completion of the 8-week follow-up period, two focus groups were conducted with the study participants. A majority of the participants expressed high acceptance of the mobile app and indicated willingness to use it in the future.

Discussion

A mobile app monitoring level of inactivity in real-time has been successfully introduced in this study. The impact of tailored messaging generated by the mobile app in response to prolonged periods of inactivity has been studied in overweight sedentary women using randomized crossover design. The results of the study demonstrated a significant impact of tailored messaging on inactivity. Comparison between “message-off” and “message-on” periods showed that there was statistically significant reduction in inactivity duration when the study particpants were receiving text messages indicating that sedentary periods exceeded healthy limits and encoraging the study subjects to move. Further analysis demonstrated that significant reduction in inactivity occurred only in Group A which receved tailored messaging during the first 4 weeks of wearing Fitbit. Participants in Group B who started receiving tailored messages only after 4 weeks of wearing Fitbit did not demonstrate decrease in inactivity after they were switched to tailored messaging. This conforms to previously described phenomenon of technological imprinting when initial patterns of new technology use are maintaned regardless of the subsequent changes in this technology.[7-9] Any change in user behavior afterward requires additonal retraining.[10,11] Our results underscore the importance of introducing fully functional mobile apps including tailored messaging from the very beginning of the intervention aimed to reduce inactivity.

Recent studies have demonstrated the importance of patient-centered delivery of the medical care tailored to individual needs, preferences, and values of the patients.[12-14] In concordance with these findings, successful implementation of the mobile app described in this study can be attributed to tailoring its specifications to preferences of the target audience and employment of participatory design principles from the beginning of the mobile app's development.[15-17] Another factor affecting high acceptance of the mobile app is that smartphones have become a ubiquitous appliance widely used in our target population.[18,19] High utility of mobile phones for health empowerment and engagement has also been demonstrated previously.[20,21]

Conclusion

A mobile app monitoring inactivity and providing a real-time notification when inactivity period exceeds healthy limits was demonstrated to significantly reduce inactivity periods in overweight sedentary women. The proposed approach is warranted for further investigation in larger group of subjects using randomized clinical trial design.

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Address for correspondence

Joseph Finkelstein, MD, PhD, Chronic Disease Informatics Program, Division of Geriatric Medicine and Gerontology, 2024 E Monument St, Baltimore, MD 21205, USA; E-mail jfinkel9@jhmi.edu