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An Integration of Health Tracking Sensor Applications and eLearning Environments for Cloud-Based Health Promotion Campaigns

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Abstract

Rapidly evolving technologies like data analysis, smartphone and web-based applications, and the Internet of things have been increasingly used for healthy living, fitness and well-being. These technologies are being utilized by various research studies to reduce obesity. This paper demonstrates design and development of a dataflow protocol that integrates several applications. After registration of a user, activity, nutrition and other lifestyle data from participants are retrieved in a centralized cloud dedicated for health promotion. In addition, users are provided accounts in an e-Learning environment from which learning outcomes can be retrieved. Using the proposed system, health promotion campaigners have the ability to provide feedback to the participants using a dedicated messaging system. Participants authorize the system to use their activity data for the program participation. The implemented system and servicing protocol minimize personnel overhead of large-scale health promotion campaigns and are scalable to assist automated interventions, from automated data retrieval to automated messaging feedback. This paper describes end-to-end workflow of the proposed system. The case study tests are carried with Fitbit Flex2 activity trackers, Withings Scale, Verizon Android-based tablets, Moodle learning management system, and Articulate RISE for learning content development.

Index Terms – *wearable sensors, data collection, e-learning, healthy living, digital user interaction, mHealth, gamification, apps, smartphones, tablets*

Introduction

There has been a remarkable growth in the use of smartphone applications recently. Smartphones are ubiquitous, versatile, and built-in with sophisticated technology. Usage of smartphone apps is not any more limited to just making calls or messaging, but spread to various activities such as social networking, emailing, and management of finances. Smartphones also have a great potential to promote healthy changes in day-to-day behavior of people. Health and fitness apps [1], the most popular ones being *Fitbit, Withings, MisFit Ray and Jawbone* are built-in with positioning and social networking capabilities like sharing on Facebook or Twitter, as well as sophisticated sensor technologies that provide physical activity related data, which can motivate people to have a healthy lifestyle and also assist researchers in improving the effectiveness and cost of health interventions.

The University of Texas at Austin College of Liberal Arts and their South Texas-based research team is conducting an evidence-based family-focused intervention (FI) [2] as part of a rural community partnership to advance Latino obesity research. The Software Communications and Navigation Systems Laboratory (SCNS) of the University of Texas at San Antonio, as a remote technology group for this study, is using technology to enhance the efficiency of such intervention.

Web-based services, Health promotion researchers commonly utilize existing systems for relatively faster and affordable technology-assisted mHealth deployments, when the major effort is in adapting and modifying known solutions for specific campaigns to enhance their impact using technology tools. Advanced personal mobile devices and applications such as tablets, mobile phones, personal trackers, mobile apps, advanced messaging systems and web-based services are a open enormous venue for enhancing human health. The number of fitness devices in the market is increasing with customers searching for the products that best suits their interests. Generally, when companies depict these products as beneficial and accurate in their estimates [3], but no study is readily provided to prove this claim.

In this research, a critical evaluation of available fitness tracking devices is performed, followed by the design and development of a dataflow protocol for collecting data from users' via health tracking sensors with the purpose of delivering healthcare to the user. We utilize Research Electronic Data Capture (REDCap) [4] as our backend database to store users' sensitive and personal data, which will also be used by health educator for monitoring and examining rural families' lifestyle on a regular basis. An eLearning environment in which users participate is also implemented for increased program availability, easy accessibility and participation. The proposed system can be viewed as a place where users can consolidate their health, fitness and relevant educational data. Most of the preexisting apps and fitness devices have application programming interfaces (APIs) which allow for the proposed system to collect data and stats. This paper also reviews previous work on similar research. Various tests are conducted to validate the protocol taking into consideration the constraints that exist in rural settings, such as limitations in Internet connectivity.

Background and Purpose

There has been a gradual shift in the mechanisms that have been put forward to improve patients' physical or mental well-being over the past 10 years [5]. mHealth platforms consist of apps and devices that seek for all kinds of health and physiological data and deliver information to patients, doctors, health educators and researchers [6]. Data that is produced by individuals is being aggregated, analyzed, and processed for informing various services as well as drawing insights about their health. These online platforms are either mobile device applications or online sites that aid and organize data streams, interactions and exchanges between users. All the platforms are usually made available to users through apps and websites.

We've performed a literature survey on existing state-of-the-art mHealth ecosystems The common parameters used by all the studies were cost, accuracy in tracking fitness data, ease of use, user interface, and API support. The research study by [7] summarized and compared the use of trackers like Withings Pulse, Misfit Shine, Jawbone Up3 and Fitbit Flex 2. From this study, Withings Pulse was the chosen best device because of its accuracy (99.90%) in terms of activity monitoring, performance, and cost as compared to other devices. The comparative study by [8] provides an evaluation of popular devices in the market like Fitbit Flex 2, Nike+ and Apple Watch. Based on [8], Fitbit Flex 2 was the most accurate device with low error rate of 1% in steps recording. Fitbit Flex 2 has API support which aids in data retrieval. On the other hand, Nike+ had 8% error in step recording and does not have API support. [11] worked on a similar research study as [8], comparing the trackers like Fitbit Flex 2, Apple Watch, Jawbone and Withings. His studies had the same conclusion as [8] with Fitbit being the most accurate devices in terms of steps and sleep measurement. Jawbone on the other hand had many false positives while the person was performing arm movement activities, such as washing dishes. The study by [9] provided a comparative report on step count, calorie count, and miles travelled on three different trackers: Fitbit Flex 2, Fitbit Charge HR and Garmin Vivo over a 14 day period. The results showed that the number of steps shown by different devices varied up to 26% due to different sensors used in each device and location of trackers on body (wrist worn or hip worn devices). [10] did a similar research as [9] on assessing the consistency of the various trackers. The trackers used in that study were Apple Watch, Fitbit, and Nike+ Band. The measurements of different devices fluctuated greatly in the range of 2-38% in terms of steps, 5-30% for distance, 2-44% for sleep duration. Most of the devices had a strong correlation in distance measurements and steps. The results showed these devices are reliable only in terms of steps and distance measurement. These studies helped us choose the best tracker for our research study. Fitbit Flex 2 was chosen as the fitness tracking device for our study, based on the ease of use, and reported accuracy in terms of fitness measurements, user interface, and API support for data retrieval.

We also performed a study on various approaches employing these fitness trackers, and their effectiveness in bringing health related behavioral and lifestyle changes in people. The purpose of the study is to compare the different state of art approaches and weigh the advantages and shortcomings of such campaigns. [12] provides detailed report on lifestyle changes of obese people with the use of Fitbit Flex devices through monthly reports showing the changes and variations in their physical activity levels. The study by [13] showed how social networking through Fitbit challenges helped in improving the health research and quality of life. A total of 44.5 thousand users were enrolled in the study. Users had positive impacts in terms of physical activity, with an increase of 1000 steps per day and 75 active minutes on weekends with each additional social tie in the user's network. The study by [14] and [16] researched on the accuracy of fitness data as reported from trackers and effectiveness in increasing the physical activity of the adults. [14] compared 9 different trackers with 50 participants from different age groups. The study concluded that smartphones and wearable devices were accurate for tracking step counts with 20% difference from the observed data. On the other hand, the study by [16] had a total of 94 healthy men and women for a 12-week intervention. The physical activity was assessed pre and post intervention and the results showed that the activity trackers were not sufficient to increase the physical activity of healthy adults. The research group led by [15] created an android health application by integrating Fitbit and dietary applications for study that involved 20 healthy adults and 16 diabetic and obese adults. The findings showed that the impact of social incentives on patients differed from that on healthy adults. The healthy adults made use of the platform to compete with other teams while the other patients made use of the medium to seek normalization and information from patient community. The results showed gaps of leveraging social fitness applications for patients. Such varied conclusions from the studies helped us in weighing possible shortcomings and choosing a health platform that would benefit the participants enrolled in the study.

The focus of our research as part of the remote technology group is to choose the tracker that best suits our needs, provides us all the relevant health and fitness related data variables, insights into personal health and learning management system that benefits the participants by providing them easy access to motivational content. The above two surveys are the part of our preliminary studies. Relevant research is being carried in the usage of cloud-based technologies for health data. Most of them are solely for observing behavioral changes in participants towards healthy lifestyle. However, there is not much focus on the real integration of health and fitness related data from trackers whose back-ends reside on heterogeneous platforms and the eLearning environments such as health related courses deployed using Moodle [18] learning management systems (LMS) and whose content is developed using Articulate RISE [19].

This paper describes end-to-end workflow of an automated data retrieval protocol, which can be integrated for health promotion campaigns. We evaluated the completeness of data collection using the Fitbit Flex2 tracker, Withings scale, and user's LMS data integrated into our proposed model.

Proposed System

A. Integrated System Architecture

A conceptual diagram of the system architecture is shown in Figure 1. The green-colored components are the components to be integrated to the system that will eventually close the loop for the health professionals while collecting, processing data and communicating with the participants. These advanced messaging tools when connected to the REDCap provide a communication channel to interact with participants.

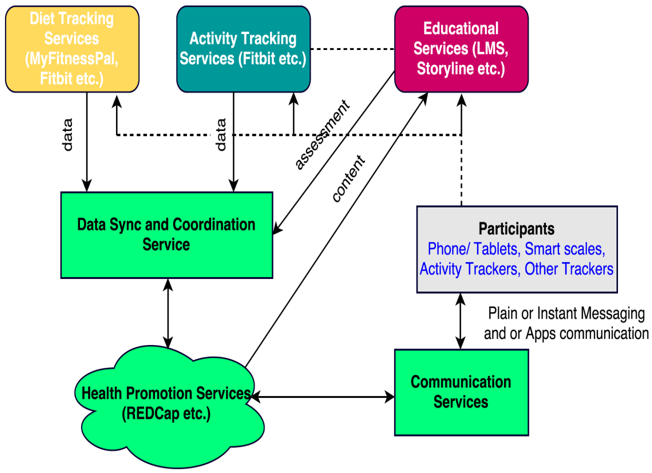

Figure 1. Integration of the complete cycle of data collection and communication with the participants

The data syncing is typically done using a Bluetooth wireless connection with a smartphone or computer application. The users can set their specific goals as reference marks and challenge themselves to achieve higher goals. Many of these applications allow tracker owners to connect with peer groups or friends, and some allow sharing data with other users. Some also have an option to connect to other third-party variable-specific (e.g. calorie counting or meal tracking app) tracking applications (e.g. MyFitnessPal [20]), that bring diet and nutrition aspects into the activity tracking picture. There exists significant value in observing diet trends over time and understanding the correlation between calorie expenditure and activity levels. During our evaluation study for activity trackers, we observed that Fitbit offers the convenience of tracking user's calorie intake; sleep duration, steps, miles, and activity minutes, etc. for the day. All this collected data can also be retrieved accurately using an API.

B. Fitness Data Flow Protocol

While the state-of-the-art lifestyle tracking systems provide excellent personalized services, they are not adequate enough for health promotion researchers to monitor their participants from a research perspective. The proposed system adapts these advanced environments for health promotion research. The personalized data can be retrieved from the involved systems and synced with the common data capture and monitoring environment shown in Figure 2 with the user's consent. The system involves wearable sensors (Fitbit and Withings weighing scale), a smartphone or tablet, study servers, and other cloud services. Each of the major components in the proposed system is intended to perform specific functions as described:

- User needs consent to our application for data collection via a webpage in which he/she can also input information as desired.
- Fitness data reaches the Fitbit and Withings applications after initial synchronization by the user via Bluetooth.
- Data is transmitted to the Fitbit and Withings servers via internret. Body weight and BMI data from Withings are synced to user's Fitbit application by using a back-end script.
- Above data is retrieved by a middleware script from Fitbit server and saved to our system in comma-separated value (CSV) or excel format. These files consist of user's physiological parameters such as activity, sleep, steps, food logs, nutrients and body logs measured by the activity tracker and the smart scale.
- These files are then stored in REDCap for data analysis and processing by the Health Educator.

The system not only collects useful health information of users, it also provides this information to users' of other application/services such as REDCap.

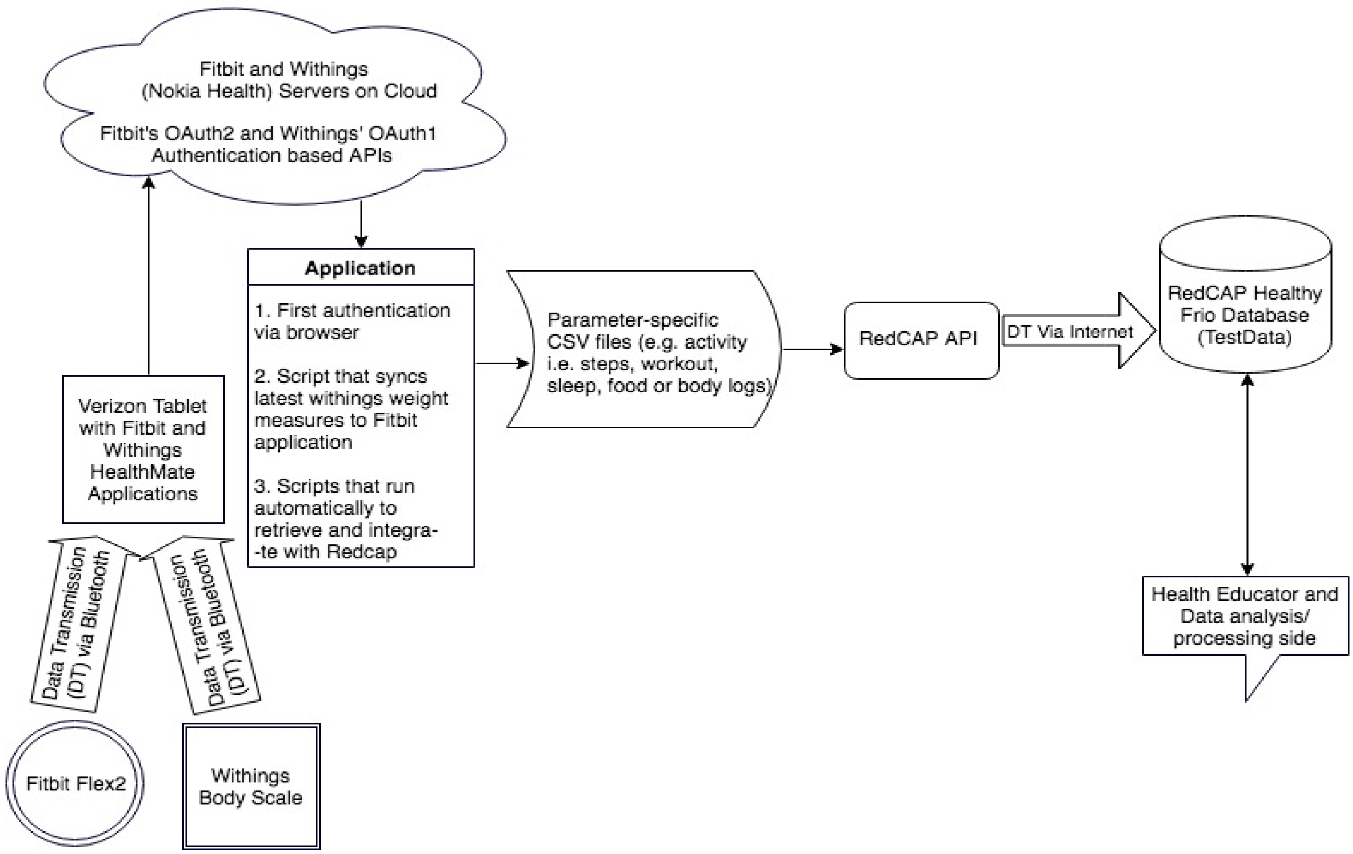

Figure 2. Data Flow Protocol and System Concept

Implementation

The backend for the proposed system's data retrieval and monitoring resides on two Amazon Elastic Compute Cloud (EC2) server instances: one for initial consent from users and a second one for the eLearning environment. APIs are used to implement data retrievals. Commonly used cloud environments like REDCap can serve as data collection and processing clouds and can be easily integrated to our system concept. These systems serve as secure web application for building and managing online surveys and databases. REDCap is specifically geared to support online or offline data capture for research studies and operations.
The initial step involves the participant authorizing the system to collect personal data. After this initial step, an automated process is used for data retrieval, collection and storage. EC2 hosting makes the system scalable based on the number of participants in the study. The activity, nutrition and other lifestyle tracking sensor data from the participants is then collected automatically from their accounts based on the ID that is retrieved during the initial registration process. An account is also provisioned for the user, which allows him/her to enter the Moodle eLearning environment.

The eLearning environment is implemented by formulating the course contents in Articulate RISE. Given that RISE does not have a capability to track the progress of the participants, Moodle is incorporated in the system concept, since it has this capability and it also provides health educators with a dashboard view of the participants' progress. The workflow of the eLearning environment is shown in Figure 3 below.

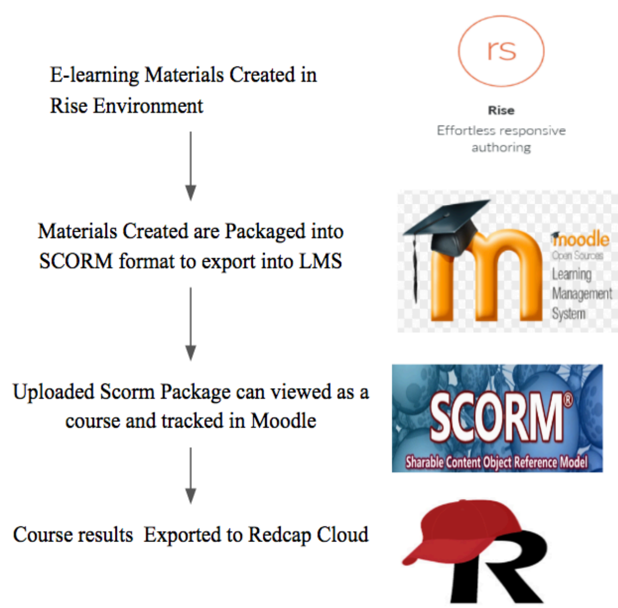

Figure 3. eLearning System Flow

The backend scripts run daily at a specific time and all the mentioned data is uploaded to REDCap for health promotion researchers for further analysis, getting insights by observing trends in their lifestyle and research studies. Researchers use the dedicated message system for providing feedback to the participants based on the analysis.
The proposed system minimizes the personnel overhead for large-scale health promotion campaigns and is scalable to assisting interventions through automated data retrieval and messaging feedback.

Integrating eLearning through Moodle to deliver Health Lessons

The idea behind integrating eLearning to educate participants comes from the fact that recent research [21] suggests that digital technologies can be used with benefits to people when they are properly designed. The aim is to develop an online course with weekly modules on healthy living, motivated through social interaction and peer learning.

As shown in the flow diagram of Figure 3, the eLearning content is created using Articulate RISE. This was chosen due to the ease of creation of health lessons, compatibility to incorporate features from other Articulate tools and integration with learning management systems. It is imperative for the research study to have a feedback on the health lessons taken by the participants. Since RISE is not capable of tracking the health lessons and progress of the participants, it is integrated with the learning management system Moodle, which provides continuous, uninterrupted access to the participants and capable of tracking and monitoring the progress of the participants.

The flow diagram of Figure 3 is described as below:

- The health educator designs the course and creates different modules using Articulate RISE and other existing Articulate tools.
- The courses are packaged into a zip file and converted to a SCORM package to make it compatible with Moodle.
- While exporting the package, RISE offers ways we would like to track the course contents:
    - Tracking based upon course completion
    - Tracking based upon quiz results
- Upload SCORM package into Moodle LMS
- Users can access the above published course from Moodle and attempt quizzes.
- The quiz results provided by the Moodle are then extracted via MySQL database into excel files and are uploaded to the centralized cloud REDCap which has the aggregated data from tracker, dietary applications and Moodle.

Experiments and Results

In theory, the proposed model aims at collecting data from various sensors and devices in an Internet of Things (IoT) healthcare environment in any data format with any number of people. This paper evaluates the performance of the system when used in the Healthy Frio Project.

A. Comparative Study and Evaluation of Trackers

Fitness and physiological data trackers vary with respect to the amount and type of data being measured or displayed on the tracker. There is wide variety of fitness trackers in the market, and the leading manufacturers like Fitbit, Garmin, and Withings, continuously keep expanding their base by releasing updated versions every year [22]. For the purpose of this study, we performed evaluations on Fitbit Flex2, Withings Go, and Misfit Ray, which are of affordable rates, yet possess advanced capabilities of measuring the variables of interest which include step counter, caloric tracker, distance counter, and sleep tracker. The functions are all similar in these three trackers, but they differ in the sensors used, algorithms, and web/mobile application.

These devices are evaluated on various criteria as shown in Table 1 from the user, researcher as well as developer's perspective. Misfit Ray does not support API. As such, the wearable sensor data cannot be easily retrieved directly or through third party applications. Fitbit Flex2 was chosen for this health promotion and intervention study because of the user interface, community/customer support, and the ability to create group challenges.

Table 1. Comparison of trackers on various criteria

Criteria	Withings Go	Misfit Ray	Fitbit Flex2
API Support	Yes	No	Yes
Group Challenges	Yes	No	Yes
Battery	Up to 6 months	Up to 4 months	Rechargeable (10 days approx.)
Data Caching (how often syncing is required)	10 days10 days	1 day	10 days
Connection with MyFitnessPal	Limited to nutrition	Unreliable	Yes
Sharing dashboard and accomplishments	Weight, blood pressure and BMI can be shared	No	Can share the dashboard to friends including steps and workout
Weight measurement	Yes	No	Can connect to a scale

B. Devices Configuration

The hardware includes wearable tracker Fitbit Flex2 for measurement of user's physical activity data, Withings Wi-Fi Body Scale [23] for body composition like weight, fat and water content and Verizon Ellipsis 10 Android-based tablet [24]. Fitbit [25], Nokia Health Mate [26] and Moodle smartphone applications are installed on the tablets. These applications perform the diet tracking, activity tracking, and educational services respectively as shown in Figure 1. The activity tracker and body scale are configured with the respective applications.

<type 'dict'>
Food log for day: {u'foods': [{u'logId': 12681510506, u'loggedFood': {u'mealTypeId': 1, u'foodId': 0, u'brand': u'', u'calories': 170, u'amount': 1, u'units': [304], u'accessLevel': u'PRIVATE', u'unit': {u'plural': u'servings', u'id': 304, u'name': u'serving'}, u'name': u'Taco Bell Crunchy Taco, 1 serving'}, u'nutritionalValues': {u'carbs': 12, u'fiber': 0, u'sodium': 0, u'calories': 170, u'fat': 10, u'protein': 8}, u'logDate': u'2017-11-19', u'isFavorite': False}], u'summary': {u'carbs': 12, u'fiber': 0, u'sodium': 0, u'calories': 170, u'fat': 10, u'water': 0, u'protein': 8}}
Number of food types entered: 1
Nutritional Summary of the logged foods: {u'carbs': 12, u'fiber': 0, u'sodium': 0, u'calories': 170, u'fat': 10, u'water': 0, u'protein': 8}
{u'mealTypeId': 1, u'foodId': 0, u'brand': u'', u'calories': 170, u'amount': 1, u'units': [304], u'accessLevel': u'PRIVATE', u'unit': {u'plural': u'servings', u'id': 304, u'name': u'serving'}, u'name': u'Taco Bell Crunchy Taco, 1 serving'}
2017-11-19
1
Taco Bell Crunchy Taco, 1 serving
170
[304]
170
12
10
0
8

Figure 4. JSON response from Fitbit food logs

C. Infrastructure Configuration

The infrastructure includes backend servers provisioned as Amazon EC2 cloud instances for the health panel and the educational panel. Initial user self-registration webpage for Fitbit data access and health educational course content are hosted on the respective panels. Health-panel uses Flask Python-based web-framework. Complete users' activity and body logs data is stored as excel files after collecting these data from Fitbit and Withings REST services. Edu-panel uses Apache and MySQL as database. All the course content consisting of lessons and users' results reside here.

D. Data Collection

The users wear the Fitbit Flex2 and measure their body composition using body scale. They will be accessing and completing the educational course content on Moodle. The applications corresponding to all these data sources upload their data to the backend through the Internet connection. Applications do cache data for some time if there is no connection to the hub. They are able to cache the detailed analyses of the data for 7 days and cumulative data for 28 days respectively. The users synchronize the data using dedicated application via Bluetooth from device to application and via Internet from application to application server (Fitbit and Withings Health Clouds). After this syncing process, the data is available for retrieval by the proposed system through the REST APIs.

For our experiments, we created an application and retrieved data stored on the Fitbit cloud for multiple users and stored it on our central hub. This was possible due to the UserID that could be extracted after initial authentication into our application by the users. UserIDs uniquely identify each user's information for further pre-processing and storage. Internally, JSON responses (user-specific but automated for multiple users) are received through the Fitbit and Withings API. An example JSON response from Fitbit for food logs is shown in Figure 4.

Users' weight data and activity data is stored on Withings Health Cloud and Fitbit Cloud separately. Hence, pre-processing also involved syncing and combining data from Withings on Fitbit application. This synchronization is also handled by our Health-panel. Therefore, the data arriving at this stage is already aggregated and is easily parsable, as shown in the JSON example in Figure 4. Such data is packaged as Comma-Separated Value format (CSV) files by extracting corresponding variables. Data from the Fitbit activity tracker, smart weighing scale and Moodle eLearning environment is further readily accessible to health promotion researchers in the form of a user-friendly dashboard on REDCap as shown in Figure 4. The implementation of mHealth platform and the automatic data capture is open in such a way that the end user data can be easily retrieved in formats or templates health educators and researchers would prefer for their further analyses.

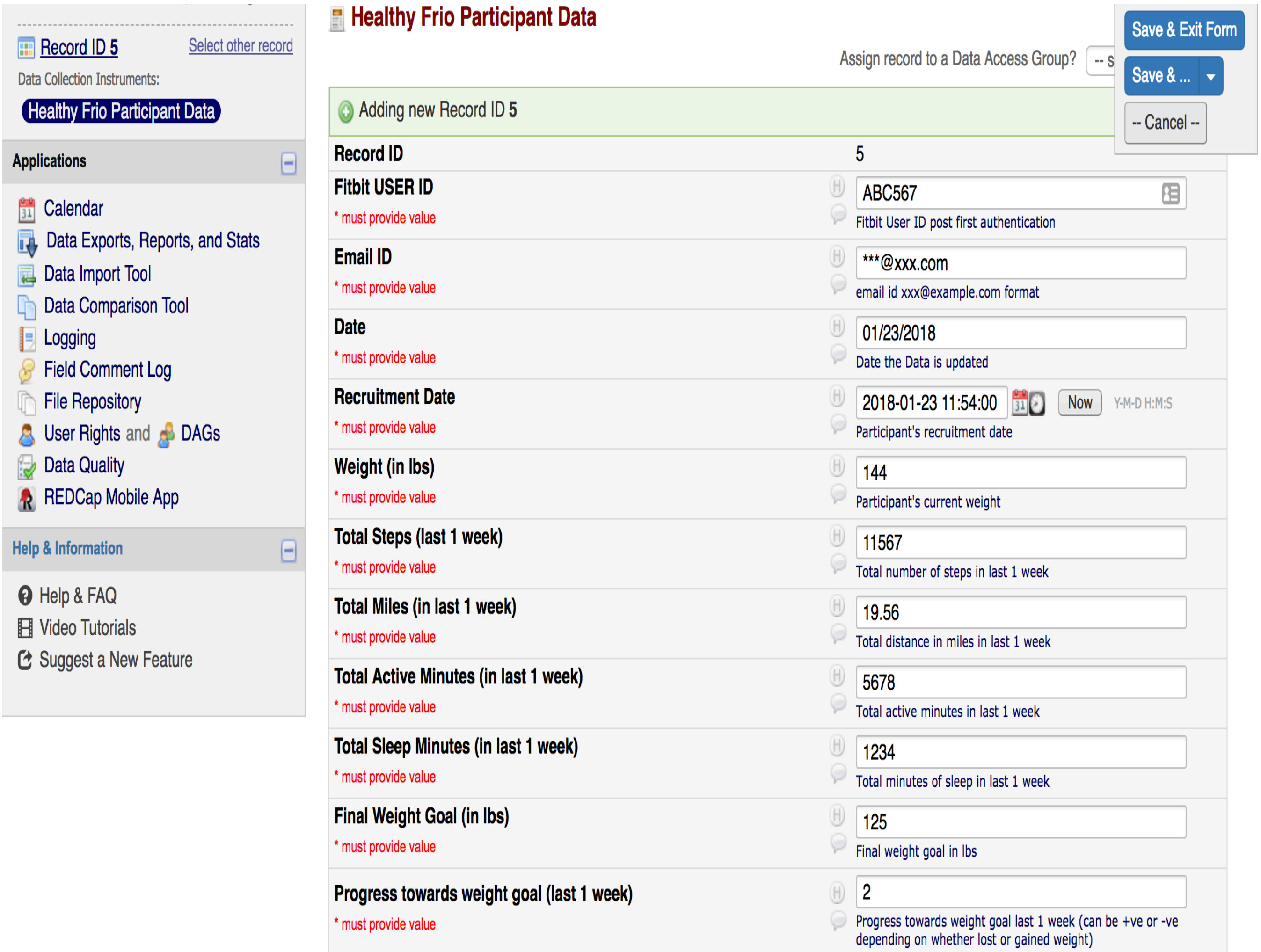

Figure 4. REDCap Data Dashboard

Conclusion

This paper demonstrates the integration of fitness and activity trackers with clinical and health education tools commonly used by researchers. The proposed system makes it possible for researchers to extract this data in a format in which they can use it for their studies. At the same time, it provides educational feedback that can help users achieve a healthier lifestyle. This research also reviewed different wearable health trackers, and discussed the criteria that these trackers need to meet in order to be used as research tools in a rural setting, saving in terms of logistics and implementation costs. Ever since the adoption of Electronic Health Records (EHR) as a potential tool [27] to improve quality of care and building large-scale health care research networks, there is lack of widespread use of EHR for research data collection. The proposed data flow model and integrated system concept aims to remove the barriers to standardized health data collection and extraction.

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