Design and Implementation of a Remotely Configurable and Manageable Well-being Study

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Abstract. Surveys are essential tools for obtaining an understanding of factors impacting a person's physical and mental well-being. Recently, surveys using face-to-face interactions have been replaced with smartphone surveys, with the added benefit of using a phone's sensor and usage data (e.g., locations, apps used, communication patterns, etc.) to collect valuable contextual information. These data collections, especially if longitudinal, often require a certain degree of flexibility and adaptability, e.g., survey questions may change over time or depend on location, demographics, and previous responses. Data collections may also be reconfigured to account for changes in the study goals or to test different intervention techniques. Finally, participant compliance should be monitored and may also lead to modifications in the data collection approach. This paper introduces a data collection tool and study design that not only collects surveys and phone sensor data, but also addresses the need for remote customization, reconfiguration, and management.

Keywords: Data collection · Well-being · Mobile surveys · Smartphone sensing

1 Introduction

1.1 Motivation and Background

Assessment of health and well-being has been an active research area for a long time [1] and researchers have been conducting studies to evaluate how factors such as mood [2], social interactions, sleeping habits, activity levels [3], perceived life satisfaction levels [4], and spiritual beliefs [5] affect the health and well-being of an individual or an entire community. Many prior studies required face-to-face interactions between study coordinator and subject, thereby limiting the geographic reach and the scale of these studies. Over the last few years, such studies have increasingly relied on mobile devices (e.g., smartphones) to support data collections [3,6], thereby enabling large-scale and wide-reaching user studies, while also ensuring increased survey compliance [7].

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Smartphones also provide other opportunities, e.g., their sensor data (GPS, accelerometer, etc.) can provide additional contextual information that can be essential for better understanding trends and outliers in survey responses (e.g., mood-related survey responses can be different when submitted from home, the workplace, when on vacation, etc.). Further, smartphones also make it easier to collect data over extended periods of time, which is often essential when the goal of such surveys is to capture well-being changes due to infrequent events, seasonal changes, etc. However, data collections using smartphones also face a number of challenges, including the need for parameterization and reconfiguration of the surveys for various reasons. For example, new insights into study design or changes in a study's objectives may necessitate a reconsideration of the survey design and questions. It may also be necessary to structure a study into different phases, each phase with different objectives, therefore, requiring that the surveys change from phase to phase. For example, the first phase could focus on sleep habits only, followed by a phase focusing on physical activities. Survey questions may also have to be configured based on the articipating subjects' demographic information and reconfigured on-the-fly based on subjects' earlier survey responses. As a consequence, this paper introduces a data collection app and study design, primarily intended for well-being studies, that provides the tools needed for remote management and re-configuration of such studies, thereby maximizing their potential values to the researchers responsible for the study outcomes.

1.2 Related Work

The movement from paper-and-pencil surveys to phone-based surveys introduces new challenges and requirements, i.e., researchers have to consider various design issues and usability characteristics [8], including timing characteristics of a user study, such as when to prompt a user for survey responses and when to provide reminders to maximize compliance if needed on top of the existing challenges also found in all forms of surveys, such as wording, question form, contexts, acquiescence response bias, straight-lining versus item specific scales [9,10], unipolar versus bipolar response scales [11], quality, and reliability and accuracy of the information captured [9,10]. User design choices also include the use of colors, fonts, response options and scales, use of images and icons, etc.

Smartphones also provide an exciting opportunity due to their built-in sensors [12], such as GPS, acceleration, proximity, temperature, or pressure, which allow us to automatically capture a wide range of contextual data. Further, other phone-related data, such as battery charge levels, the number of text messages exchanged or phone calls made and received, etc., can also provide important insights into the contexts of the user responding to a survey and can therefore be used to compensate for data collection inaccuracies and biases (such as recall bias, memory limitations, and inadequate compliance that comes from self-reports) [7].

Advances in wearable and pervasive computing technologies [13–15] also provide opportunities for the continuous tracking of various physiological data.

Examples of such sensors include respiratory inductance plethysmography (RIP), electrocardiograph (ECG) and galvanic skin response (GSR). These devices also face various challenges, such as user discomfort and sensing inaccuracies due to improper sensor placement [16], therefore, most studies using such sensors focus on controlled environments (e.g., in laboratories or a doctor's office) instead of collecting data in subjects' home or work environments [3,6]. sensing inaccuracies due to improper sensor placement [16], which demands in person interaction between subject and study coordinator [14,17], therefore, most studies using such sensors focus on simulated or controlled environments (e.g., in laboratories or a doctor's office) for a limited period. Software development kits, such as Apple's ResearchKit also increasingly facilitate the integration of surveys with data collected from physiological sensors using devices, such as Smart Watch, etc.

One of the efforts more closely related to ours was presented in [3], where the authors performed a mobile health study on 48 students for 10 weeks using Android phones. During the study, they continuously captured opportunistic phone sensor data, along with the phone-based user surveys. In this study, subjects are required to respond to surveys immediately upon prompting, which can be difficult in some scenarios, e.g., when the subjects are in exams, sleeping, or driving [17]. While the focus in [3] has been on phone sensing and the use of typical well-being surveys, other efforts suggest that a comprehensive well-being study should also consider life satisfaction [4], spiritual belief [5], and day reconstruction [18] surveys, further demonstrating the need for more comprehensive and flexible data collection tools.

1.3 Contributions

The primary contributions of this paper are (1) the design and implementation of a flexible data collection tool that provides easy remote management and reconfiguration options (Sect. 2), (2) the design of a concrete well-being study using this tool (Sect. 3), and (3) a preliminary analysis of data collected in a brief well-being study performed at the University of Notre Dame (Sect. 4), with a focus on the investigation of changes in sleep habits and mobility levels of students during and after the final weeks of a semester.

2 The WellSense Smartphone-Based Data Collection Tool

2.1 System Architecture

Like other existing data collection applications, the primary goal of *WellSense*, our proposed data collection tool, is to provide a mechanism to perform large-scale well-being studies using modern smartphones. However, WellSense also simultaneously monitors a variety of contextual information (using phone sensors, resources, and usage patterns) and provides mechanisms for remote data collection management, including the ability to redesign and reconfigure an ongoing study "on-the-fly". Figure 1 shows the high-level system architecture of WellSense, consisting of a mobile survey and monitoring app, a cloud-based check-in server and database, and a management web portal. Study participants will receive survey requests via the mobile app (implemented for both the iOS and Android platforms) and survey responses are transmitted over the network to a *check-in server*, which is responsible for processing and storing the incoming data in a global database, where each subject or device has a unique identifier and all survey responses are time-stamped. In addition, WellSense also monitors various phone sensors and phone activities that are collected locally on the mobile device and transmitted to the server via an automatic nightly upload (i.e., "check-in"). The web portal is the study administrator's primary tool to manage a study, e.g., to monitor compliance and response rates, but also to modify study design, including changes to the survey questions, modifying the timing of survey requests, or the frequency of survey requests. Study participants may also use the web portal to track their own progress and compliance.

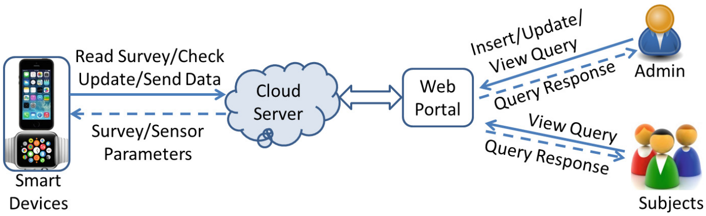

Fig. 1. System diagram of WellSense.

Study participants have full control over which surveys they wish to respond to, i.e., they can skip entire surveys or individual questions of a survey (e.g., when a survey may cause emotional distress or privacy concerns). While a survey is "open", participants can also revise and resubmit their responses. At the end of a survey, the app informs the participant about the number of questions answered and skipped and at that point the participant can decide to revisit questions or to submit the responses. If the survey fails to upload to the server (e.g., due to a lost network connection), the participant can submit the survey at a later point, without loss of data. Once a survey has been submitted, all responses, their corresponding question identifiers, and timestamps, along with a survey identifier and user identifier are stored on the cloud server. Currently, we use the Parse (www.parse.com) server, primarily due the ease of integration of the server with mobile applications. Each survey response is stored as a new row in the database, together with the identifiers described above. Given survey ID, question ID, user ID, and timestamps, it is easy for a study administrator to monitor compliance or to detect patterns that may indicate difficulties in the study, such as poor response rates for a specific survey or question, which can be due to the content or the timing of the survey or question. Parse also supports push notifications, which allows a study administrator to push alerts to one or more participants, e.g., when their compliance is low.

2.2 WellSense App Design

The primary purpose of the phone-based surveys is to assess the well-being of a subject based on various contexts and activities during different times of the day. For example, to measure the sleep quality of a subject we can administer a sleep survey in the morning that consists of sleep-related questions, such as the number of hours slept, the perceived sleep quality, how many times a participant woke up during the night, etc. However, the survey app is generic enough to be used for any kind of surveys and studies, in the well-being and health domain and beyond.

Fig. 2. Main menu of the WellSense app on (a) Android and (b) iOS.

Figure 2 shows screenshots of the WellSense app for both the Android (Fig. 2(a)) and iOS (Fig. 2(b)) platforms. These screenshots demonstrate two primary design choices:

- **Survey Categories:** Well-being (and other health-related concerns) are affected by a variety of factors, e.g., sleep quality, mood changes, social interactions, and unusual events encountered. Therefore, the app supports the distribution of multiple surveys that fall into one of these categories. Icons are used in addition to textual information to clearly distinguish between different survey categories.
- **Surveys Status and Survey Timing:** On the Android platform, all surveys to be answered during the current day are listed in chronological order and *open surveys* (i.e., surveys waiting for the participant's response) are shown in bold text, while *closed surveys* (i.e., surveys not yet available or surveys that are no longer available for responses) are shown in a gray color and can no longer be tapped. The iOS version uses a slightly different approach: it uses three sections to distinguish between *current* (open), *future* (not yet open), and *past* (already closed) surveys.

Fig. 3. Response layout for (a) Button, (b) Slider and (c) Textbox questions.

Another design choice is how participants can respond to survey questions and this depends on the type of the question. For example, Fig. 3 shows screenshots of three main types of responses supported in the WellSense app: *buttons*, *sliders* (or scales), and *textboxes*. The textbox input is the most flexible in that participants are able to provide any type of response, while the others have limited input options.

2.3 WellSense Survey (Re)Configuration

Surveys are designed and distributed via the web portal and the Parse-based cloud server. Surveys are stored in the database in a two-level hierarchy. At the first level, survey meta-information, consisting of survey category, identifier, timing (day/time when survey is open), and a boolean field called "active" that allows the study administrator to turn on or off a survey, is stored. Each survey links to information stored at the second level of the hierarchy, including a set of questions (identified by question IDs), response types, and response options. Existing surveys can, therefore, be reconfigured anytime and a subject's WellSense app checks into the server each night (during a randomly selected time between midnight and 6 am) to see if surveys or questions have been added, removed, or modified. In that case, all changes are fetched and the next day's list of surveys will reflect these changes.

2.4 WellSense Survey Notifications

The WellSense app also supports a *notification mechanism*, which can be used to remind participants to respond to open surveys. We call the period when a survey is available for responses the *active period*, e.g., a *sleep quality* survey may have an active period from 7 am to 9 am every morning. During a survey's active period, the phone will generate up to four notifications spaced equally, i.e., an active period of 2 h will generate a notification every 30 min (e.g., a survey with an active period from 10 am–12 pm will trigger notifications at 10 am, 10.30 am, 11 am, and 11.30 am). Once a participant replies to a survey, further notifications for this survey will be suppressed. A participant can choose to respond to a survey either via the app's main menu or by tapping the survey's notification.

2.5 Phone Sensors and Phone Usage Data

Smartphones (and similarly wearable devices) provide an opportunity to collect additional information besides survey responses. Specifically, the sensors built into modern smartphones provide the tools needed to collect information, such as physical activity, location, mobility patterns, social interactions (e.g., using proximity sensors), and heart rate (in the case of wearables). In addition, phone usage patterns and trends can also provide highly valuable context information that can be associated with the changes in survey responses. Such data include browsing histories, communication habits (calls, texting), social networking activities, and app usage. Table 1 shows several examples of data that can be collected on a smartphone. In the case of WellSense, these data are collected from a separate app that runs continuously in the background. This app, called CIMON (Configurable Integrated Monitoring Service) [19], collects data along three axes: (1) system data (that includes information such as battery status or the type of network the phone is currently using for communication), (2) sensors (a phone's built-in sensors), and (3) user activities (such as browsing history, communication, and app usage). CIMON stores all collected data in a database on the phone and uploads these data every night into the server. Similarly to the survey data, all uploads rely on secure handshake protocols and encryption using AES. While the amount of data collected by CIMON can be very large (see sampling rates in Table 1), the data can be extremely useful when analyzing and interpreting survey responses. CIMON also supports *labeling*, which allows participants to log additional contextual information that can be useful for later analysis. For example, a study on the physical activity levels of rehabilitation patients could allow participants to record whenever they perform exercises or

Table 1. Different types of sensor and usage data captured by a phone

Sensor/Data name	Type	Sampling period
Memory, CPU load, CPU utilization, Battery, Network traffic, Connectivity status	System	1 s
Geo-location	Sensor	10 s
Accelerometer, Magnetometer, Gyroscope	Sensor	100 ms
Proximity, Pressure, Light, Humidity, Temperature	Sensor	1 s
Phone activity, SMS, MMS	User activity	1 s
Screen state, Bluetooth, WiFi	User activity	3 min

spend time outside. These labels are considered to be ground truths while performing supervised learning on collected survey and sensor data.

3 Design of a Well-being Data Collection

This section describes the design of a well-being data collection effort built around the WellSense app. The goal of our work is to obtain a better understanding of personal, work-related, social, environmental, and other factors impacting the physical and mental well-being of individuals.

3.1 Pre- and Post-Surveys

For all kinds of data collection efforts, it is very common to perform pre-participation (entry) and post-participation (exit) surveys. Pre-participation surveys can be used to verify that potential study subjects meet inclusion criteria, to ensure a specific desired distribution of the study population, and to establish a baseline for each subject. Exit surveys are often used to gather participants' experiences and feedback for future studies or to collect additional information that was not obtained during the data collection phase.

In our efforts to collect data to study participants' well-being, we utilize two types of surveys in addition to the WellSense data collection (both types are simple web-based surveys; future versions of WellSense will integrate them into the mobile app):

– **Resource Assessment Survey.** The primary goal of this survey is to get an idea of the types of devices used by the subjects, and whether there is any need for resource (e.g., loaner devices). Subjects are also asked for information, such as their class and exam schedules, project deadlines, demographic information, and health issues and concerns (e.g., pre-existing conditions), which provides us with additional context.
– **Pre-Study and Post-Study Surveys.** The primary goal of these surveys is to collect baselines of well-being in terms of current health, fitness, perceived stress, perceived success and satisfaction, loneliness and other social concerns [3], and sleep quality [20] before and after the study.

3.2 Using WellSense for a Well-being Study

The purpose of the phone-based surveys is to assess the well-being of a subject based on various contexts and activities during different parts of the day. Table 2 shows the list of surveys and their question types that we considered in our implementation to capture various contexts and activities that affect personal health and well-being. Table 2 also shows the schedule for these surveys, where "M", "Su" and "S" represents Monday, Sunday, and Saturday, respectively. Apart from "Life Satisfaction" and "Spirituality", all other surveys are answered daily. The "Mood Survey" [2] looks for positive and negative factors impacting mood as well as stress and fatigue levels. While often ignored in other studies, we also consider "Spirituality", since this can also have a great impact on overall well-being.

Table 2. Phone surveys and their schedules

Survey category	Question type and Scale	Day (Time)	Active period (h)
Mood [2]	Rank ordering	M-Su (10 am, 2 pm, 6 pm)	2
Sleep quality [3]	Slider and Likert interval	M-Su (8 am)	3
Social Interaction [3]	Dichotomous, Multiple choice, Bi-polar semantic differential	M-Su (9 pm)	2
Day Reconstruction [18]	Ratio, Open-ended, Multiple choice, Interval	M-Su (10 pm)	2
Life satisfaction [4]	Uni-polar rating	S (12 pm)	12
Spirituality [5]	Uni-polar rating	Su (6 pm)	6

4 Case Study

To test the feasibility and the validity of our remotely configurable and manageable mobile health and well-being approach, we conducted a brief case study on 28 healthy subjects (college students). The study ran for four weeks, covering the end period of spring semester, in order to measure anxiety and stress levels before, during, and after exam time.

4.1 Subjects

Subjects were invited via emails, stating the goals of the study and the requirements for the subjects if they decide to participate (note that no incentives were provided). The study consisted of 12 male and 8 female undergraduate students (average age of 20y 7 m with SD = 8 m) and 7 male and 1 female graduate students (average age of 29y 4 m with SD = 2y 7 m). Only 6 of the subjects used their own phones, all others received loaner devices from our lab. Out of the 28 subjects, 2 used iOS-based devices, all others used Android.

4.2 Method

The study ran over four weeks, where each subject began to use WellSense about 1–2 weeks before finals week and then continued data collection for another 1–2 weeks after finals week. Over the 4 weeks, each subject was required to respond to different types of surveys (as shown in Table 2). They were also asked to provide labels, such as “Meeting”, “Entertainment”, “Walking”, and “Biking”. At the same time, the CIMON mobile framework continuously collected various types of phone data (as described in Table 1). In total, more than 17,000 survey responses and over 100 million samples of phone sensor data were collected. A study coordinator frequently monitored the progress of study (i.e., data collection) via the web portal, varied study parameters (such as sampling frequencies, survey administer time and active period, and survey questions), and provided feedback to subjects over email.

4.3 Results

Prior work has shown that sleep patterns can have a significant impact on well-being and health [3,6], therefore, one of our goals is to investigate the sleep patterns captured by the WellSense study. From Fig. 4 (showing the sleep patterns of one specific participant), we can observe that sleep duration falls when class is ending since during that time the subject had three projects and homework deadlines. Sleep duration increases during study days (when students are somewhat more relaxed), but then drops again before the two exams on May 4 and May 5, and finally, go back to normal after exams end.

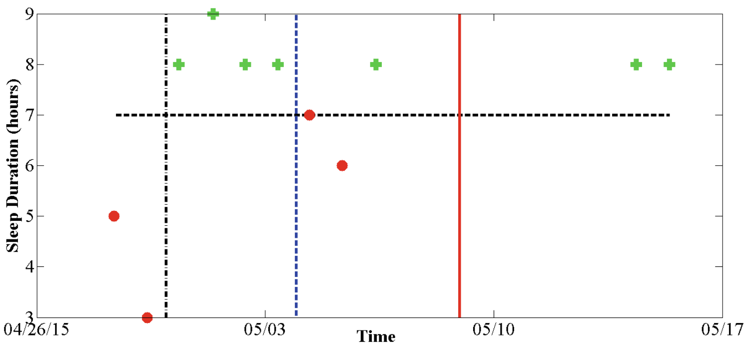

Fig. 4. Sleep duration variation of an individual over the entire study period. The black horizontal dashed line represents the base line of sleep duration (7 h) for the subject based on her response using the PSQI scale [20] in the "Pre-study" survey. The vertical dash-dot black (left most), dashed blue (middle), and solid red (right most) lines correspond to the last day of class (April 29), end of study days and start of exam period (May 3), and end of exam period (May 8) for the Spring 2015 semester. All vertical lines are drawn at 11:55 pm, i.e., at the end of a day. The red colored circles below the horizontal dashed line and green colored plus (+) markers above the horizontal dashed line represent the sleep duration below and above the base line. (Color figure online)

Next, we investigate activity and mobility of subjects. In Fig. 5, we observe low activity and few location changes during exam week. From the "Resource Assessment" survey, we know that this specific subject had an exam from 10:30 am to 12:30 pm on May 8. It seems that before May 8, the subject stayed primarily in his dorm room, preparing for his exam. We observe that from 3:20 pm to 6 pm on May 7, there is no data collected, followed by continuous data streams until midnight that day. It appears that the subject turned off the data collection app, but the phone was still on since the battery level also declined during that period. From May 7 midnight to May 9 at 11 am, we again did not receive any data. This is because the subject had an exam and turned off the phone for all of May 8 until the next morning, since during that period, there was no observable degradation of the battery charge level.

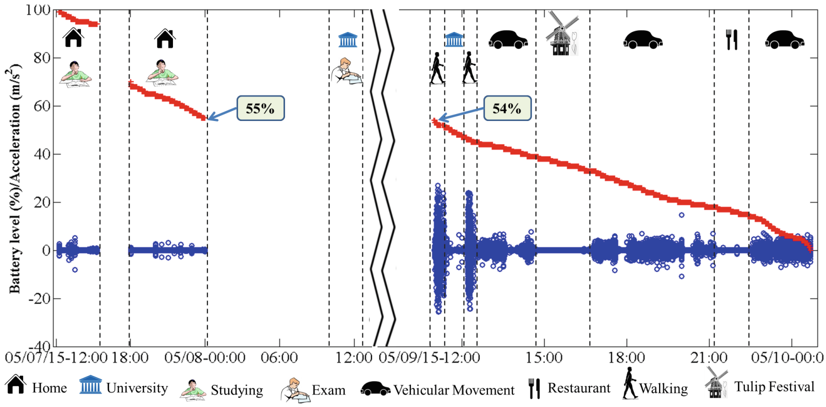

Fig. 5. Variation of battery level (red plus "+" markers) and activity level in terms of magnitude of three axis of acceleration (blue circles) over the study period for an individual. Very low variations of acceleration (**var** $\approx$ 0) and static geo-coordinates indicate that the subject is not moving; large variations in acceleration, but small changes in location indicate that the subject is walking; small variations of acceleration (**var** $>$ 0), but fast changes in location indicate that the person is moving in a vehicle. (Color figure online)

In Fig. 5, we can also see that on May 9 from 11 am to 11:20 am, the subject was walking from his home to university, spent the time period between 11:20 am and 12 pm at the university, then walked between 12 pm and 12:29 pm, commuted in a vehicle between 12:29 pm and 2:40 pm, participated a festival in Holland, Michigan from 2:40 pm to 4:43 pm (based on GPS coordinates, event calendars, and the subject's "Day Reconstruction" survey), then drove again until 9:17 pm, when the subject spent time at a restaurant in Chicago until 10:30 pm, then finally followed by another drive (towards home) until 12.41 am. The graphs in Figs. 4 and 5) are based on all the surveys that the subjects have taken and the sensor data that their phones have captured. This is an example, showing that the combination of survey data and sensor data can be used to reconstruct a subject's day, providing us with information that can be essential to understand the factors impacting a person's health and well-being.

5 Conclusions

Preliminary analysis from the continuous sensor data and subjects' survey responses shows the feasibility of a remote mobile health and well-being study that does not require fact-to-face interaction between subject and study coordinator. This study can be both managed (i.e., monitoring study progress) and configured (i.e., changing various study parameters) independent from the locations of the subjects. The ability to re-configure an ongoing study provides us (i.e., study administrators/coordinators and researchers) more flexibility to change critical study parameters, without disrupting the study. Further, this paper provides examples of how the collected data can be used to analyze factors relating to health and well-being, such as sleep patterns, mobility patterns, social and community events, and time periods of varying degrees of anxiety and stress.

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