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Wireless Sensor-Dependent Ecological Momentary Assessment for Pediatric Asthma mHealth Applications

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Abstract

Pediatric asthma is a prevalent chronic disease condition that can benefit from wireless health systems through constant symptom management. In this paper, we propose a smart watch based wireless health system that incorporates wireless sensing and ecological momentary assessment (EMA) to determine an individual's asthma symptoms. Since asthma is a multifaceted disease, this approach provides individualized symptom assessments through various physiological and environmental wireless sensor based EMA triggers specific to common asthma exacerbations. Furthermore, the approach described here improves compliance to use of the system through insightful EMA scheduling related to sensor detected environmental and physiological changes, as well as the patient's own schedule. After testing under several real world conditions, it was found that the system is sensitive to both physiological and environmental conditions that would cause asthma symptoms. Furthermore, the EMA questionnaires that were triggered based on these changes were specific to the asthma trigger itself, allowing for invaluable context behind the data to be collected.

Index Terms

mobile health (mHealth); wireless health systems; ecological momentary assessment; mobile applications

I. Introduction

According to the Asthma and Allergy Foundation of America, approximately 24 million Americans have asthma, and each year, approximately 2 million emergency room (ER) visits occur each year as a result[1]. Additionally, the World Health Organization has found that asthma is under-diagnosed and under-treated and restricts individuals' activities across their lifetime[2]. Asthma attacks can not only be life-threatening for the patient, but also extremely costly through the resulting hospital or ER visits. Thus, managing asthma effectively early on, with minimal interruption, can potentially improve individuals' quality of life.

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Furthermore, since uncontrolled asthma in children aged 5–17 years account for a loss of 10 million school days and costs caretakers over $726 million per year[3], asthma self-management is most important during these years of an individual's life.

Clinicians have long been interested in finding an effective means for monitoring and controlling pediatric asthma symptoms in the real world to prevent asthma attacks. For instance, personalized mobile-based applications[4] have been explored to communicate Asthma Action Plans (AAPs)[5] to teens. This technology presents an opportunity for drastic reductions in preventative care costs; if patients are exposed to triggers that exacerbate their asthma, oftentimes their clinician won't be able to provide immediate recommendations. As a result, novel mobile-based techniques such as Ecological Momentary Assessment (EMA) have been developed to determine asthma exposures within the community[6]. Clinical techniques and mediums for administering EMA have been shown to be reliable and accurate, as EMA has a much better correlation between the actual event and what was recalled by the patient[7]. Based on this prior research, this paper describes a solution that combines EMA with a wireless health system for real-time symptom management of asthma through mobile and smart watch based applications.

The smart watch application utilized in this study, the Biomedical REAl-Time Health Evaluation (BREATHE) platform[8], is designed to monitor activities and behaviors of children who suffer from asthma. The long term goal is to reduce asthma attacks while the patient is in the field through continuous monitoring and appropriate AAPs. By expanding upon our preliminary work to determine the overall risk of an asthma attack[8], this study investigates new strategies for obtaining a higher level of patient care through intelligent asthma monitoring of physiological, environmental, and psychosocial behaviors. The application presented here describes a new implementation of EMA using sensor and smart watch based triggers as well as new strategies for disseminating and visualizing collected information. More importantly, the larger goal of this application is to create a platform that can educate the patient, reduce the probability of the patient worsening their asthma symptoms, prevent ER visits due to asthma attacks, and provide individualized AAPs and recommendations.

II. Related Work

There has been significant research on real-time health monitoring applications[9;10]. In particular, wireless health systems that target asthma are becoming more prevalent[11]. For instance, Dieffender et al.[12] used a combination of a wireless spirometer, chest band, and wrist band to combine real time physiological data with environmental data from ozone and volatile organics compound sensors for monitoring patients with asthma. After feasibility testing for sensor acquisition, the authors concluded that real-time, objective measures of physiologic parameters, environmental measures, medication use, and patient reported outcomes would greatly enhance management of chronic and acute asthma. However, the study did not incorporate EMA methodologies to measure patient outcomes and psychological behaviors such as perceived stress, a known asthma trigger.

Other mobile applications in pediatrics that have utilized EMA methods have found that wearable sensing technologies, such as those described above, are necessary for a comprehensive asthma wireless health system. Specifically, a previous EMA study[13] in which a mobile phone and waistworn accelerometer were used to monitor physical activity among children found that children do not carry mobile phones during exercise. This is because mobile phones are too bulky and uncomfortable to wear while running in smaller children. Thus, it is difficult to measure physical activity and provide appropriate EMAs at opportune times after exercise, which is an important asthma trigger. In order to develop a successful application for continuous monitoring of pediatric asthma symptoms, one must design a platform that meets compliance standards such as this while being able to provide feedback and EMA questionnaires to the individual or caregiver through mobile devices. This warrants the use of other technologies, such as smart watches, where wearability and feedback can be provided.

Wireless sensing mechanisms such as smart watches cannot feasibly detect all potential asthma triggers in pediatrics, such as psychosocial behaviors (e.g. perceived stress). Consequently, wireless health systems for pediatric asthma require context of the situation in order to prevent false alarms of a potential asthma attack and provide psychosocial context. While remote detection of psychosocial behaviors may be difficult to detect via sensors alone, frequent assessments offer the opportunity for understanding regular "microprocesses," the interplay or cascade of cognitive, affective, and behavioral variables over short intervals of time[14]. In particular, these microprocesses are able to show how behavior varies over time in response to different environmental and physiological contexts. For example, when assessments of these behaviors are combined with relevant sensor data, we can better identify the individual factors and patterns that are associated with worsening asthma symptoms and higher risks of asthma attacks. Given these requirements, in this paper we propose the design of a new sensor-based EMA system for pediatric asthma, where the goal is to bridge the gap between existing wireless health and EMA systems to create a single wireless health platform that can integrate wireless physiological and environmental sensing data with context-sensitive self-reports for comprehensive pediatric asthma monitoring.

III. Methods

The BREATHE application described in Hosseini et al.[8] and expanded upon here is a wireless sensor system for pediatric asthma. Specifically, the original system consists of a smart watch, spirometer, and environmental sensors for continuous monitoring of potential asthma triggers for a child (Fig. 1). In this study, we incorporate EMA questionnaires with the BREATHE system to introduce three new techniques for asthma disease monitoring: context-dependent health risk triggers, EMA survey trigger inter-application integration, and real-time data monitoring and visualization of traditionally-unavailable automated wearable sensor data.

Following a patient monitoring system design like the one presented in Gao et al.[15], the BREATHE application allows for continuous monitoring of a child's risk of an asthma attack. Our previous model introduced a core asthma application that continuously collected

physical activity, heart rate, environmental measures such as fine particle contaminants, and lung function data in real time, and uploaded the data to a cloud-based server via an online representational state transfer (REST) application programming interface (API). The sensor data is then combined with several online sources to provide traffic, weather, and air quality information. The cloud server system then utilized a trained machine learning model based off of a random forest classifier to evaluate incoming data and determine the overall risk of an asthma attack (high, medium, or low risk). These classifications are then returned every minute to the smart watch in the form of a real-time asthma risk level dragon animation (Fig. 2). The focus of these continuous risk level alerts is to provide the child with real-time alerts under warranted (dangerous) conditions that can exacerbate the child's asthma symptoms and cause asthma attacks. This form of feedback was designed for children, as they are engaging and can be easily interpreted as different risk levels.

To support EMA in the core application, we implemented new REST API routes to detect different sensor-based asthma triggers, such as increased heart rate, increased particulate matter and dust density due to air contamination, and high energy expenditure due to physical activity. These specific triggers detect specific patterns that indicate potentially dangerous situations related to asthma exacerbations throughout the day. At the time of the detected activity, the application visually alerts the patient to perform an EMA questionnaire specific to the above asthma trigger.

The machine learning model trained using accelerometer data that comes from the watch and is tuned for that particular childs modality of motion. The model will learn to observe high energy expenditures of the child to detect exercise. Rather than using an in-lab developed wearable device, the BREATHE platform was designed using an off-the-shelf Motorola Moto 360 Sport[16]. This was chosen over custom-built devices as it is widely available and the application can be expanded to all commercially available smart watches, thus increasing its acceptability among potential users. More importantly for data collection, this wearable allows low-power simultaneous listening of heart-rate, accelerometer, gyroscope, and GPS data - ultimately providing a more accurate and long term estimate of the individual's current physiological behaviors.

In addition to the physiological sensors, the BREATHE platform model also relies on environmental sensors. The wireless environmental sensors (dust density and particulate matter sensors) of the BREATHE platform are designed to be either placed statically in the home or school environment, or carried by the individual throughout the day. The BREATHE application will automatically connect and begin recording data from these sensors when in range. To wear the devices, the sensors can be attached to the user's belt or clothing. Finally, the wireless spirometer used in the BREATHE platform collects lung function data on demand when the individual uses it, and the BREATHE application triggers an EMA survey to collect information from the child that can validate the level of asthma the child is experiencing after an asthma risk level change.

IV. Context-Dependent Health Triggers

The smart watch application continuously collects data from multiple physiological and environmental streams. However, it is unable to collect psychosocial data and provide contextual information of the collected sensor data. Thus, we address this issue by implementing four new distinct health and environmental triggers described below that initiate specific EMA questionnaires related to the changes in sensor data.

A. Explanations of Triggers

There are four potential triggers that can identify specific physiological and environmental asthma triggers. To this end, we represent these triggers via flag signals delivered via the BREATHE API: spirometer use, local air quality worsening, increased energy expenditure, and increased heart rate. The BREATHE application evaluates the incoming sensor data from the individual based on multiple criteria, all simultaneously and in near real-time (with a 1 minute average latency between sensor variation and server response). Each trigger flag represents a different risk category or potential asthma exacerbation. We categorize these risk flags in the following sections.

1) Spirometer—The spirometer trigger is perhaps the simplest; we trigger a spirometer-specific questionnaire automatically within a few minutes after the patient uses his or her spirometer sensor. The spirometry device records whether the forced expiratory volume in one second (FEV1) and peak expiratory flow rate (PEF) measures of lung function were accurately collected after each use, which is recorded on the cloud-based server. This questionnaire can be custom-built and is tied to any spirometer use throughout the day since the sensor is only used when the asthma risk level changes. The exact times of the spirometer and corresponding EMA survey that is launched are both recorded on the server.

2) Air and Environmental Quality—To trigger an EMA survey related to air quality changes detected by the environmental sensors, a trailing moving average of fine (less than 2.5 micron diameter) air particle contaminant concentration is used. Note that there does not exist any specific dust concentration standards related to health, as most health-based standards rely on ambient air pollution on an absolute level such as those defined by the Environmental Protection Agency[17] and World Health Organization[18]. Furthermore, many health-based standards rely on *regional* ambient air pollution, such as those reported via AirNow.gov[19]. The concentration-response functions also greatly vary depending on the composition of the air pollution and size distribution of the particles. Thus, the following equation was empirically determined after several laboratory-based tests under various exposure conditions to determine whether a significant change in ambient air exposure due to local pollution has occurred:

$$Trigger = \begin{cases} C > 5, & \text{if } C < 10ug/m^3 \\ C > 0.5\mu, & \text{if } C < 10ug/m^3 \end{cases} \quad (1)$$

where μ is a 2 minute trailing moving average of the dust density measurements, and C is the current environmental contaminant concentration measured in absolute micrograms per cubic meter. If the dust trigger from the cloud based server returns a “true” based on the above equation as the air exceeds a dangerous level of dust concentration, the patient is alerted via the smart watch that he or she is at a potentially high risk of an asthma attack and triggering an environmental specific EMA questionnaire.

If poor air conditions persist, static pollutant sensing may present a risk of repeating false positive triggers; thus, by using a simple conditional model with a defined threshold of 10 ug/m^3 (a low dust concentration value) avoids triggering “minor” absolute dust concentration changes that are large percentages in low pollution environments. For example, a change from 1 ug/m^3 to 3 ug/m^3 is a large change percentage-wise, but is generally considered insignificant when studying causes of environmentally triggered asthma symptoms[20]. As a result, the above piece-wise monitoring function is able to avoid these false positive triggers given the range of dust concentration changes that can be observed.

3) Energy Expenditure—Using a moving average of the energy expenditure calculation adopted from Yamada et al.[21], the cloud based server uses the energy expenditure in combination with heart rate and the other sensors to make a risk evaluation. The energy expenditure trigger follows the model used by similar remote health monitoring systems[22] that relates accelerometry to metabolic equivalents (METs)[21]. Specifically, for this trigger, the energy expenditure of patient is directly calculated from the last N accelerometer measurements. This “windowed” energy calculation is denoted by K_n and is calculated via the following equation:

$$K_n = \sqrt{\sum_{i=1}^{n} x_i^2 + \sum_{i=1}^{n} y_i^2 + \sum_{i=1}^{n} z_i^2} \quad (2)$$

where N is based on averaged 5 Hz accelerometer measurements over a 5 second window, and x, y, and z are the accelerations in each respective direction. The 5 second window offers a large enough time frame to capture slow movements in order to obtain a good estimate of the particular activity type[21]. The model has a calibrated baseline energy and triggers the energy expenditure flag when there is a significant change in the the most recently calculated energy values. The threshold is set based on the metabolic equivalents (MET) values at baseline for the user’s age group, and triggers an EMA survey related to physical activity when the user exceeds 5 METs. This threshold is based on METs related to moderate intensity aerobic exercise.

4) Physical Activity Trigger—The individual’s elevated heart rate levels are measured relative to the person’s baseline while at rest. A high heart rate will lead to a higher risk levels of an asthma attack, as previously observed in Hosseini et al.[8]. Note that an elevated heart rate can be triggered by behavioral factors other than exercise, such as stress. Based on the patient’s age and resting heart rate, we calculate the increased heart rate trigger by estimating the heart rate reserve[23] using the following equation:

$$Trigger = 0.5(HR_{max} - HR_{rest}) + HR_{rest} \quad (3)$$

where 0.5 corresponds to an aerobic fitness level of 5–8 METs, HR_{rest} is the individual's resting heart rate collected during baseline data collection, and HR_{max} is the maximum heart rate that is predicted based on the child's age. In particular, HR_{max} for children is defined as[23]:

$$HR_{max} = 208 - 0.7(age) \quad (4)$$

5) Trigger Timing—All four of the sensor based EMA triggers described previously can be triggered at anytime during usage; the application polls the server for both the asthma attack risk level and EMA triggers. If a sensor based EMA trigger is high, the relevant questionnaire is launched shortly after on the mobile phone. The phone collects the EMA surveys as it provides larger screen for more detailed and custom questions. An example of how the heart rate trigger fires an EMA questionnaire in the BREATHE application can be seen in Fig. 3.

The heart rate (among all other sensors) is collected during each "Sensor On" cycle described in Fig. 4 below. For the BREATHE system to be able to rely on the heart rate data from the smart watch for accurate measurements, it is important to know the accuracy of the measurement for each sample collected. The accuracy of the heart rate measurements depends on the performance of the smart watch and the fit of the wearable to the user's wrist. It has been found in a previous study[24] that the Moto360 smart watch used in this study has a heart rate accuracy of 92.8% when compared to an Onyx Vantage 9590 pulse oximeter, a clinically validated sensor for heart rate and blood oxygen saturation. Though we did not directly evaluate other watches in this particular study, other devices can be used as well for the application wearable component of the platform since the photoplethysmography (PPG) sensor utilized is the same across smart watches.

The watch operates on a 45 second on/off sensor cycle, in which the all sensors are online for 10 seconds collecting data. This provides a sufficient window for the most recent physiological and environmental data to be collected without compromising significant battery life during sustained sensor use throughout the day. The REST API requests including sending sensor data to the server, risk level assessments, and EMA triggers are collected at the end of each cycle. We will further discuss how we provided power optimization for the smart watch at the end of this paper.

The survey collection is managed via another on-board mobile application known as the PRISMS EMA application. This EMA application listens for incoming API connections from the wearable to determine whether a questionnaire should be launched on the mobile device based on the user's sensors and history. For example, a heart rate warning trigger launches a heart-rate specific EMA survey on the mobile device while simultaneously

alerting the user on the smart watch. This engages the user and provides personalized data collection during asthma exacerbation conditions.

V. EMA App-To-App Integration

BREATHE and PRISMS are two tightly integrated applications. The EMA application is fully functional even when it is completely offline and will cache/queue survey responses locally until connectivity is re-established. By keeping the EMA application separate from the BREATHE platform, the EMA surveys can leverage local device reminders that do not depend on Internet connectivity and allow the user control over when to generate the scheduled or “non” random notifications. Furthermore, if the participant is temporarily out of range of the mobile phone, the sensor data is still able to accumulate and transferred to the server once connection is re-established. This allows for continuous sensor data collection when the user cannot take EMA surveys or use their phone, such as during exercise[28].

Traditionally, EMA questionnaires are either collected at random times, or regularly scheduled times, from the user during the day. Having regularly scheduled data collection is key to understanding behavior trends, however, it can lead to less insightful or honest results from the individual. Although one may feel confident in his or her ability to recall memories accurately, research in the self-report domain has shown otherwise[25;26]. The goal of the sensor based EMA triggers is to implement a technique that optimizes time and data-collection pertinence to a particular event. Through the use of context-dependent survey triggers, not only can the information collected from the individual be customized given particular scenarios that are related to asthma, but it can also be collected at the time of the event. This can lead to higher accuracies of reported information as well as more personalized data collection given known asthma triggers.

As of 2015, there have only been 4 of 209 asthma-related applications available that provide location dependent environmental information to the user[27]. To provide location dependent information, the BREATHE application incorporates the time stamp and location in every sensor based EMA trigger that is generated on the device. If the triggered EMA survey is not responded to by the user, this information is recorded and provided to the clinician on the cloud based server for review of compliance at a later time. Each survey is configured to provide contextual information given the particular sensor based trigger. For example, if a drastic increase in heart rate is detected using the heart rate sensor trigger, an EMA questionnaire similar to the one presented in Fig. 5 is launched.

A. Real-time Monitoring of Sensor Data

In addition to the smart watch user interface, the BREATHE application also allows for the data trend lines to be viewed on the mobile phone (Fig. 6). This is important for both the caregiver and user to be able to monitor their data in real time, and to help them understand the relationship between increased asthma attack risk levels and their current situation. To this end, data is securely transferred to our cloud based server and is conversely sent to the mobile to view the data via a REST API when requested for viewing. By default, the last 100 measurements and corresponding time stamps are displayed to the user.

The clinicians can also review the incoming sensor data by accessing the cloud based server (https://www.breatheplatform.com). Specifically, the cloud based server of the BREATHE application provides a secure login only accessible by clinicians and researchers to access the data collected by the BREATHE application in real time. The clinician can export the data relevant to his or her patients and view the results outside of the platform for further analysis.

VI. EMA Surveys and Compliance Measures

The EMA application is linked to the BREATHE application and is a customized client of the mobilize lab's mobile data collection (MDC) platform that sends data to a separate Ohmage server. Participants in the study are able to login into the EMA application on the smartphone and are authenticated and authorized via Ohmage server-side APIs. In this flow, the EMA app retrieves the PRISMS study instruments (surveys) from the APIs, presents them to the user (based on a trigger, or random notification), and saves or queues the responses locally until connectivity is available to upload them to the server.

Since each wireless sensor and EMA measurement is timestamped and geo-located, the EMA application has a significantly reduced need to ask questions about where or when the patient was doing something using the EMA surveys. Through selective location history around device usage, survey completion can be reviewed by the clinician as part of the patient's overall behavioral or asthma attack risk[8] to deliver a more accurate timeline of the events, resulting in less guess work and a better ability to deliver highly personalized care. When each survey request on the smartphone is logged and sent to the Ohmage server, the clinician can retrieve a patient's history to observe patterns of non-compliance for both missed surveys and missed medication dispensation. The clinician can then use this information to determine why such a pattern of non-compliance is occurring.

A. EMA Timing

EMA questionnaire notifications come in two varieties: scheduled and random. The scheduled notifications are setup during an "app initialization" process. During this process, participants are directed to schedule or select a 'morning' time that is convenient for them to complete a set of questions about how they slept. Different scheduled times can be selected for a weekday versus a weekend. In addition, there is a user scheduled 'after-school' time set for a reminder to complete a survey about how school went. During a weekday, there are also two random periods in which notifications are randomly delivered before the end of the day.

Notification or reminder messages are timed to engage the participant so that they become more compliant with taking EMA surveys. The timing of data collection via surveys is done after a short delay from the actual activity (determined by the sensor measurements returning from escalated to normal levels). This reduces the amount of disturbance from the actual application, while still retaining the higher level of temporal accuracy in the user's responses. To this end, when a reminder is ignored, another notification is triggered 4 minutes later. If the participant fails to complete the survey within another 4 minutes, a final notification reminder is triggered 2 minutes later. A window of 10 minutes is provided for

the participant to begin a survey. Once the EMA timing window is closed, the reminders for the particular survey are cleared, or wiped off the device. If the participant fails to answer all the questions on the survey, a partial response is accepted and submitted to the Ohmage server automatically. Though this scheme can lead to a high number of notifications, but this pilot test is also meant to assess the participant's ability to comply with the planned protocol, so the notification times are iteratively reduced given the level of compliance achievable. Finally, an example of a question in the after school survey is shown below in Fig. 7.

The triggered questionnaires from the wireless sensors are not bound by the EMA timed response protocol described above. Specifically, a triggered questionnaire will remain active until the user is engaged with the EMA application, at which point the appropriate survey is presented to the user.

B. Mobile EMA Data Analysis

The EMA data is sent and stored on the separate Ohmage server, which can be readily viewed or exported for analysis by the clinician. In the Ohmage platform, a research study is referred to as a campaign, which represents a set of surveys or data streams collected for analysis together. There are four generic tools for analyzing the EMA data. The first analysis tool that Ohmage provides is called "Campaign Manager", which enables an authorized user such as a clinician to view raw survey responses and export patient survey data similar to the BREATHE platform (Fig. 8). The second analysis tool is a monitoring tool that allows a clinician to view how the data is coming in. The third is an R-based tool called "Plot Tool", which the clinicians can use to explore the data in more fine grained detail. Finally, the fourth tool is an "Interactive Dashboard" visualization portal that allows clinicians to see data through the following mediums (Fig. 9): 1) a geographical map, 2) two types of bar graphs, 3) pie charts, 4) view images that may have been collected by the mobile device, and 5) a word map. The clinician is able to filter these graphs by data type through interactive dials.

To achieve higher rates of compliance, the EMA application also provides several strategies via a custom "Personalized EMA Compliance" dashboard on the smartphone's user interface (Fig. 10). This dashboard allows clinicians to see if sharing application analytics data with the user can promote study compliance and adherence through social engagement. The application provides participants with a "compliance view" so that the user can see how many surveys have been successfully completed. A compliance percentage value is then determined using the number of questionnaires answered – which varies by participant due to the number of sensor-based triggered surveys. To encourage compliance, a compliance level of 80% is deemed good, a moderate compliance is between 50% and 80%, and a low compliance is considered as answering less than 50% of the questions provided. A daily and weekly view of compliance is presented to the user. When a low compliance is detected, the participant is allowed to share a reason to the clinician.

VII. Power Optimization of Combined System

Since the smart watch has the least amount of battery life compared to the smart phone even with the above EMA and BREATHE applications running simultaneously, power-saving mechanisms and variable-rate sensor sampling that enables repeated device sleep cycles are implemented to allow for full day use of the system. The extended battery life using these mechanisms enables unobtrusive and virtually-continuous sensing throughout the day, without requiring the patient to frequently recharge his or her smart watch. Furthermore, the continuous sensing enables the patient to receive appropriately triggered EMA questionnaires and alerts on the smart phone when exposed to high risk asthma attack conditions.

With a small battery capacity of 300 mAh on the smart watch, the following steps are taken to conserve battery life of the wearable and offload tasks to the mobile device when appropriate (which typically has a battery size greater than 2000 mAh). First, we offload the encryption and HTTP request processing to the smart phone since it has a much larger battery. In addition, when the wearable is in low-power mode, with the application running in the background and the user interface screen off, we reduce the sampling cycle to once every minute and tie it to an automatically-invoked clock update Android system call. While the application silently runs in the background in this state, we are able to obtain a battery life of ~16 hours, as we allow the smart watch to sleep as much as possible when not collecting data. This is shown in Fig. 11 below; we obtain an average battery power loss of roughly 1% every 9.1 minutes.

The information extractable from the battery profiling in the above diagram can be directly related to the BREATHE sensor timing figure illustrated in Fig. 4. This profiling doesn't describe causal analysis of battery decay (in that we can't conclude that sensor A caused an X% decrease in battery life), but we can do causal analysis. To relate these images, the gray bars are matched to the time when the sensors are active, the red bar indicates that the application is open, and the purple segments indicates that the application is active (and not sleeping). Note that the purple bars in the above diagram extend slightly beyond the gray. This difference is manifested in the time required to fulfill the sensor post requests to the server. The 'GCM' in the figure indicates an active message exchange between the wearable and mobile device. By allowing the wearable to extensively rely upon the mobile device for web requests, we are able to obtain a significantly extended battery life of the overall system itself. When tested, the biggest detriment to the battery life comes from frequent user disruption of the watch's ability to sleep.

VIII. Discussion

This study illustrates how context-dependent sensor triggers can be integrated into the sensor based BREATHE application to deliver a more personalized level of care to patients. Additionally, enabling external access to sensor data can enable data mining for a more accurate and contextual prediction of when patients are at risk of having an asthma attack. By using a linked wearable device, the application can notify the user (and clinician if

needed) in the case of a potentially threatening situation given various potential physiological, environmental, and psychosocial asthma exacerbations.

If a patient fills out an EMA survey immediately after a period of strenuous activity such as exercise that resulted in an asthma attack, both the patients' responses and data collected can be used for future classification of events that precede the attack. If these events can be better identified, we can be able to identify and alert users prior to potential asthma exacerbations. These improvements can enable applications that use this technology to provide scalable and cost-saving interventions for asthma attack prevention.

Rather than relying on the very limited questions that could be given the small screen size of the smart watch, the EMA surveys are developed on the smart phone so that the user can answer a variety of questions, such as: "What have you been doing in the last 30 minutes?", or if the user's heart rate is high, we can deliver a variety of context-sensitive questions that ask the user about shortness of breath or rapid breathing symptoms. This allows our system to take advantage of both the smartwatch's wearability and convenience for sensor collection during asthma exacerbations such as exercise, as well as the larger screen of the smart phone.

One challenge mentioned in previous work was needing the mobile phone to be on the user for data collection to work correctly[13]. These are noisy systems, and there are conditions where there is noise in the data and the data stream may be disconnected at any time in a real world system. Noise management and data continuity were studied in detail in our some of our other work[8;29]. However, the native Android wearable and mobile phone used in this system enables native queuing of data transmissions with only minor configurations so that even if the patient is temporarily out of range of the mobile phone, the sensor data is saved on the smart watch and accumulates until the connection is re-established. This is important for ensuring completeness and continuity of sensor data, another advantage of using a combined smart watch and smart phone based application.

Another advantage of this system is that whenever a survey trigger is recorded, the application makes a note of the time that it occurred. This prevents duplicate or high-proximity events from triggering a response to the user. Each trigger time is recorded and can be made visible to the clinician. This allows for easy synchronization between the EMA and BREATHE applications.

While applied specifically to symptom management in pediatrics who suffer from asthma, the sensor based EMA trigger models demonstrated in this paper can be generalized and applied to other diseases conditions and self-management mobile applications. Wearable devices offer significant advantages for low-cost and continuous monitoring of diseases and health risk in patients, enabling a level of care previously not possible by clinicians. With these applications, clinicians can have a virtual "fly on the wall" view of how diseases affect individuals within the community, and how to better prevent hospital readmissions or worsening symptoms. In addition, the data from EMA and wireless sensors can provide an objective diary of the user's behavior and environmental exposure, which can potentially allow clinicians to diagnose risky situations before they become dangerous to the patient.

IX. Future Work

Compliance in EMA and wireless health studies is often a concern. For example, when non-random collection schemes such as the one in this paper are used, missing assessments have a greater potential to bias the survey result set[14]. Furthermore, much of the responsibility for data collection by EMA surveys relies on the user to complete assessments in response to different activities and asthma exacerbations. Thus, future work on this platform will focus on ways to improve patient compliance and adherence to the EMA application through methods such as gamification.

One of the key components of the application is through the environmental data collection. The particulate matter and dust density sensors in the system provide low-cost mechanisms for monitoring environmental air conditions in real time; however, while these devices are portable, they need to be exposed to the patient's environment (and not stored in a backpack or pocket). Thus, to improve feasibility and adoption of environmental sensor use, we plan to develop more portable devices that can be more easily worn on the user and collect environmental data with similar levels of battery life and concentration accuracies.

Future work will also include more extensive testing and data collection with children who suffer from asthma. This will be performed as part of a planned pilot clinical trial funded by the National Institute of Biomedical Imaging and Bioengineering (NIBIB) Los Angeles (LA) Pediatric Research using Integrated Sensor Monitoring Systems (PRISMS) Center. In addition, future developments of the application will be to include AAPs to the smart watch and smart phone based on the EMA and sensor data, as well as improving compliance and adherence through user engagement and iterative feedback from users.

X. Conclusion

In this paper, we presented three new approaches to asthma care and tracking: personalized and context-dependent health risk triggers, EMA cross-application integration, and real-time data monitoring and reporting of traditionally unavailable sensor data by clinicians. By delivering a higher level of real-time asthma monitoring, we are able to not only improve the level of context in the data collected for a multi-faceted disease condition, but also improve patient engagement through condition-dependent alerts and EMA questionnaires. Furthermore, the data resulting from the EMA surveys is more informative than if they were scheduled at regular intervals, as they occur during relevant events related to potential asthma exacerbations. This can improve the level of personalization, user engagement, and potentially the compliance of system use for asthma self-management. It can also improve the clinician's ability to monitor their patient's asthma disease conditions and provide better preventative care. If this system is deemed effective in our planned future clinical trial, it will become a low-cost and scalable self-management tool for pediatrics who suffer from asthma.

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References

1. Vahdatpour, A., Amini, N., Sarrafzadeh, M. Pervasive Computing and Communications (PerCom), 2011 IEEE International Conference on. IEEE; 2011. On-body device localization for health and medical monitoring applications; p. 37-44.
2. World Health Organization. Asthma fact sheet no 307. 2008. updated november 2013. Available from: http://www.who.int/topics/asthma/es
3. Sharma GD, Gupta P. Pediatric asthma. 2013
4. Burbank AJ, Lewis SD, Hewes M, Schellhase DE, Rettiganti M, Hall-Barrow J, Bylander LA, Brown RH, Perry TT. Mobile-based asthma action plans for adolescents. Journal of asthma. 2015; 52(6):583–586. [PubMed: 25494553]
5. National Heart Lung and Blood Institute. Expert panel report 3: guidelines for the diagnosis and management of asthma. full report 2007, national asthma education and prevention program, us department of health and human services, national institutes of health. 2014
6. Smyth JM, Soefer MH, Hurewitz A, Kliment A, Stone AA. Daily psychosocial factors predict levels and diurnal cycles of asthma symptomatology and peak flow. Journal of Behavioral Medicine. 1999; 22(2):179–193. [PubMed: 10374142]
7. Moskowitz DS, Young SN. Ecological momentary assessment: what it is and why it is a method of the future in clinical psychopharmacology. Journal of psychiatry & neuroscience: JPN. 2006; 31(1): 13. [PubMed: 16496031]
8. Hosseini, A., Buonocore, CM., Hashemzadeh, S., Hojaiji, H., Kalantarian, H., Sideris, C., Bui, AA., King, CE., Sarrafzadeh, M. Wearable and Implantable Body Sensor Networks (BSN), 2016 IEEE 13th International Conference on. IEEE; 2016. HIPAA compliant wireless sensing smart watch application for the self-management of pediatric asthma; p. 49-54.
9. Wu, W., Au, L., Jordan, B., Stathopoulos, T., Batalin, M., Kaiser, W., Vahdatpour, A., Sarrafzadeh, M., Fang, M., Chodosh, J. The smartcane system: an assistive device for geriatrics. Proceedings of the ICST 3rd international conference on Body area networks; ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering); 2008. p. 2
10. Pantelopoulos A, Bourbakis NG. A survey on wearable sensor-based systems for health monitoring and prognosis. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews). 2010; 40(1):1–12.
11. Marcano Belisario JS, Huckvale K, Greenfield G, Car J, Gunn LH. Smartphone and tablet self management apps for asthma. Cochrane DB Syst Rev. 2013; 11
12. Dieffenderfer J, Goodell H, Mills S, McKnight M, Yao S, Lin F, Beppler E, Bent B, Lee B, Misra V, Zhu Y. Low power wearable systems for continuous monitoring of environment and health for chronic respiratory disease. 2016
13. Dunton GF, Dzubur E, Intille S. Feasibility and performance test of a real-time sensor-informed context-sensitive ecological momentary assessment to capture physical activity. Journal of medical Internet research. 2016; 18(6):e106. [PubMed: 27251313]
14. Shiffman S, Stone AA, Hufford MR. Ecological momentary assessment. Annu Rev Clin Psychol. 2008; 4:1–32. [PubMed: 18509902]
15. Gao, T., Massey, T., Sarrafzadeh, M., Selavo, L., Welsh, M. Participatory user centered design techniques for a large scale ad-hoc health information system. Proceedings of the 1st ACM SIGMOBILE international workshop on Systems and networking support for health-care and assisted living environments; ACM; 2007. p. 43-48.
16. Motorola.com. Moto 360 Sport. 2016. https://www.motorola.com/us/products/moto-360-sport
17. EPA.org. NAAQS table. 2016
18. World Health Organization. Ambient (outdoor) air quality and health. 2016

19. AirNow.gov. Airnow AQI forecast. 2016
20. Koenig JQ, Mar TF, Allen RW, Jansen K, Lumley T, Sullivan JH, Trenga CA, Larson TV, Liu L-JS. Pulmonary effects of indoor-and outdoor-generated particles in children with asthma. Environmental health perspectives. 2005:499–503. [PubMed: 15811822]
21. Yamada Y, Yokoyama K, Noriyasu R, Osaki T, Adachi T, Itoi A, Naito Y, Morimoto T, Kimura M, Oda S. Light-intensity activities are important for estimating physical activity energy expenditure using uniaxial and triaxial accelerometers. Eur J Appl Physiol. 2009; 105(1):141–152. [PubMed: 18853176]
22. Suh MK, Chen CA, Woodbridge J, Tu MK, Kim JI, Nahapetian A, Evangelista LS, Sarrafzadeh M. A remote patient monitoring system for congestive heart failure. Journal of medical systems. 2011; 35(5):1165–1179. [PubMed: 21611788]
23. Mahon AD, Marjerrison AD, Lee JD, Woodruff ME, Hanna LE. Evaluating the prediction of maximal heart rate in children and adolescents. Research quarterly for exercise and sport. 2010; 81(4):466–471. [PubMed: 21268470]
24. El-Amrawy F, Nounou MI. Are currently available wearable devices for activity tracking and heart rate monitoring accurate, precise, and medically beneficial? Healthcare informatics research. 2015; 21(4):315–320. [PubMed: 26618039]
25. Bradburn NM, Rips LJ, Shevell SK, et al. Answering autobiographical questions: The impact of memory and inference on surveys. Science. 1987; 236(4798):157–161. [PubMed: 3563494]
26. Tourangeau, R., Rips, LJ., Rasinski, K. The psychology of survey response. Cambridge University Press; 2000.
27. Wu AC, Carpenter JF, Himes BE. Mobile health applications for asthma. The Journal of Allergy and Clinical Immunology: In Practice. 2015; 3(3):446–448. [PubMed: 25725939]
28. Dunton GF, Whalen CK, Jamner LD, Henker B, Floro JN. Using ecologic momentary assessment to measure physical activity during adolescence. American Journal of Preventive Medicine. 2005; 29(4):281–287. [PubMed: 16242590]
29. Hojaiji H, Kalantarian H, Bui AAT, King CE, Sarrafzadeh M. Temperature and humidity calibration of a low-cost wireless dust sensor for real-time monitoring. In Proc. of 2017 IEEE Sensors Applications Symposium, pp. 2017:1–6.

Fig. 1.

The BREATHE platform consists of a mobile phone, smart watch, wireless spirometer sensor, and two environmental sensors for particulate matter and dust density monitoring.

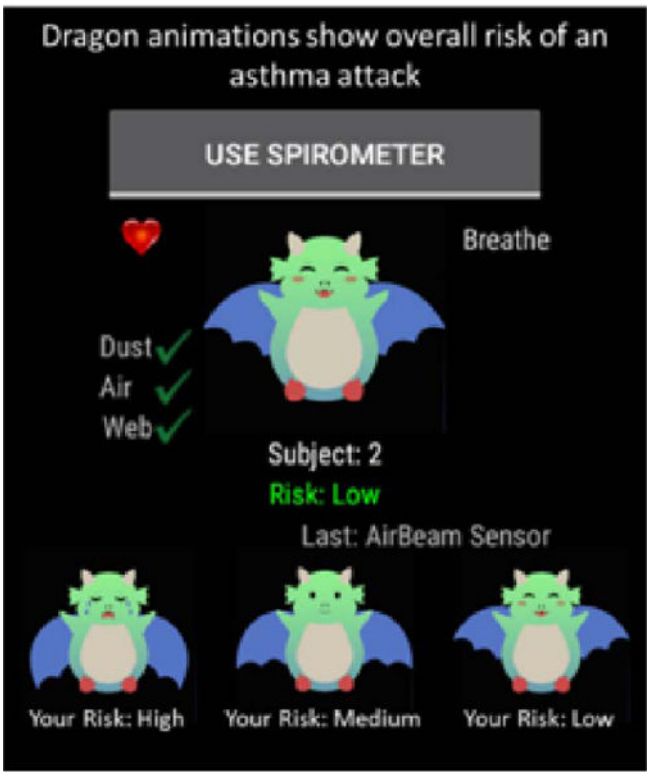


Fig. 2.
Wearable user interface screen on the smart watch that provides animated asthma risk levels in real-time.

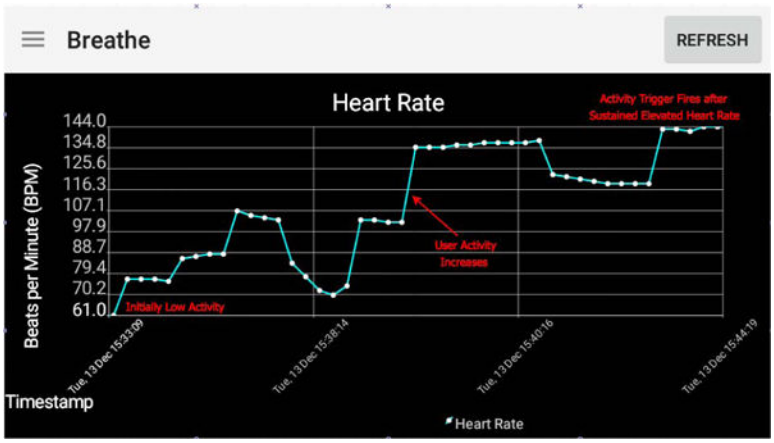


Fig. 3.

Mobile view of the heart rate changes that would cause an sensor based EMA trigger to return a “true” from the server.

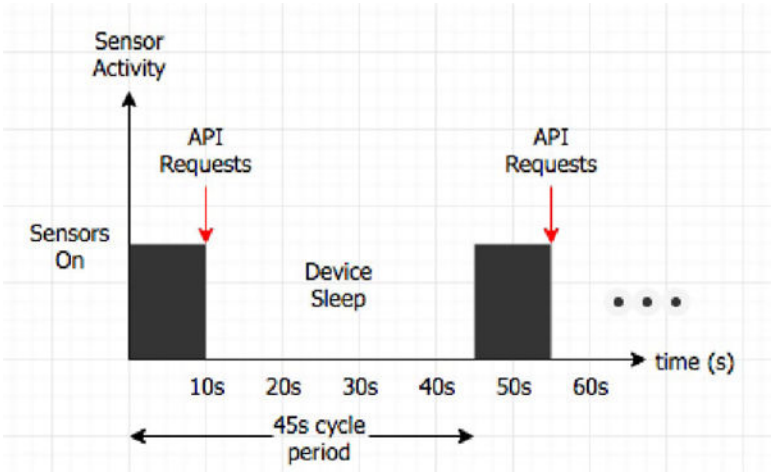


Fig. 4.

The BREATHE timing diagram, showing that the 45 second period shifts to 1 minute when the device screen is off, though sensor data are still collected in the background.

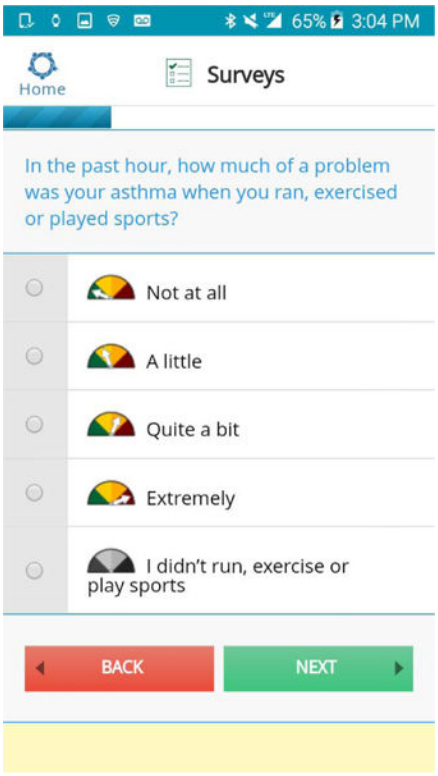
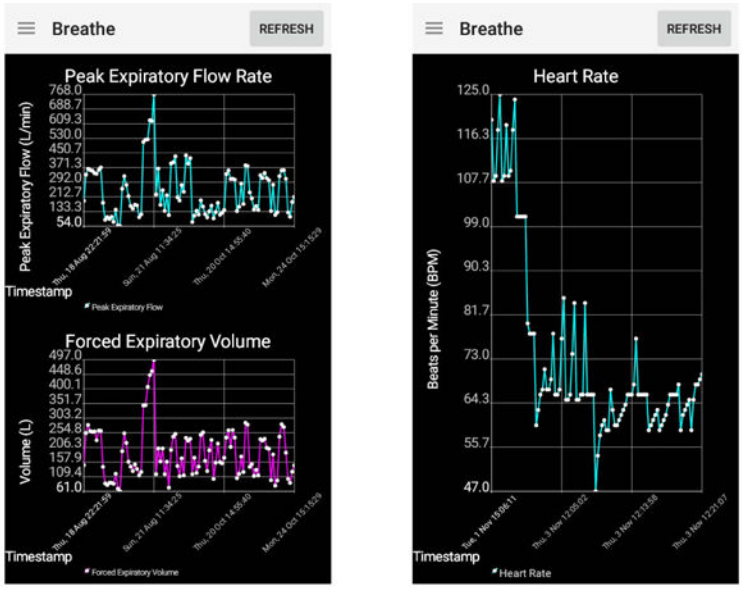


Fig. 5.
PRISMS survey application for activity-specific questionnaires, showing the EMA survey for the heart rate sensor based trigger.



(a) Data trend lines of the current spirometer readings.

(b) Data trend lines of the current heart rate readings.

Fig. 6.

Examples of data trend lines viewable by the user or caregiver on the BREATHE mobile application.

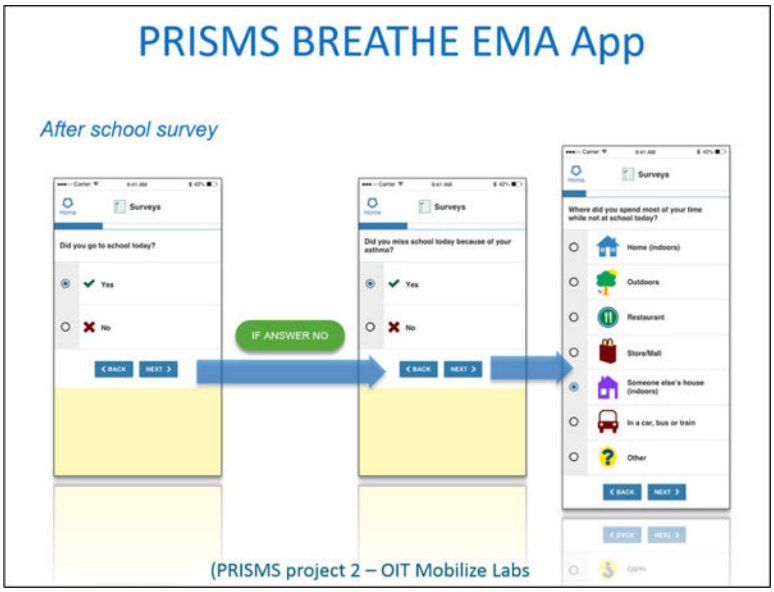


Fig. 7.

Regularly-scheduled after school survey screen shots show patient workflow through the PRISMS application.

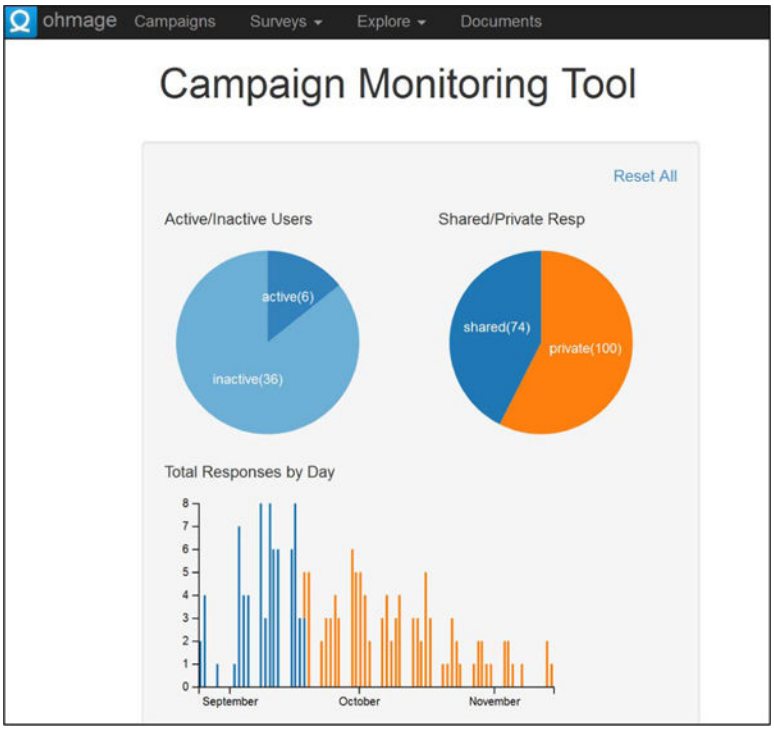


Fig. 8.

Clinicians can tweak the campaigns in the Campaign Manager so that they see the most patient responses.

Fig. 9.

Clinicians can visualize the incoming EMA data through several different graph views on the Interactive Dashboard: geographical maps, bar graphs, pie charts, images collected by the smartphone, or a word map.

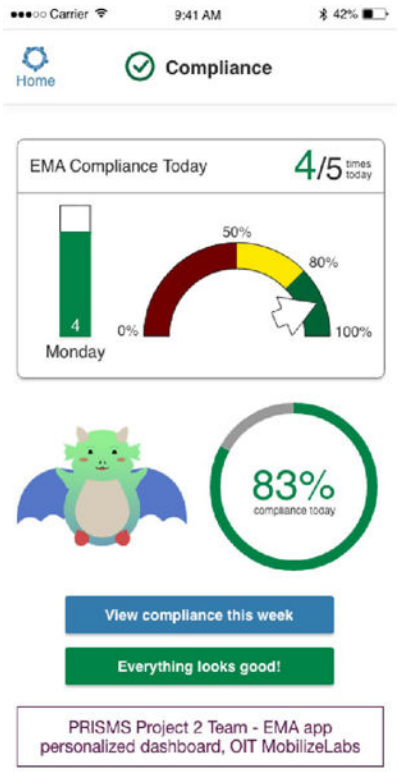


Fig. 10.

Compliance screen showing completed survey percentages with BREATHE dragon user interface.

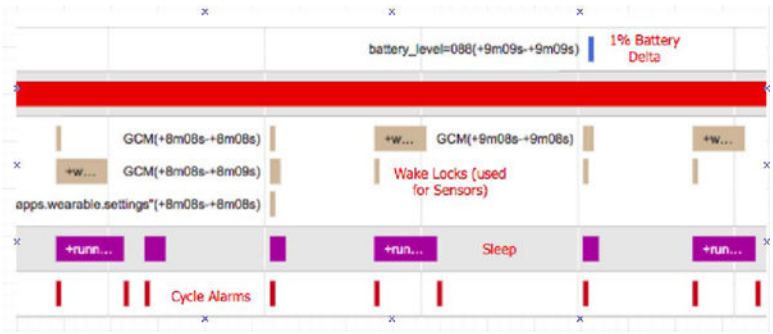


Fig. 11.

Android battery profiler showing a section of live operating-system level activity on the Android smart watch.