Marquette University
e-Publications@Marquette

Master's Theses (2009 -) Dissertations, Theses, and Professional Projects

mPeer: A Mobile Health Approach to Monitoring PTSD in Veterans

Casey James O'Brien
Marquette University

MPEER: A MOBILE HEALTH APPROACH TO MONITORING PTSD IN VETERANS

by

Casey J. O'Brien, B.S.

A Thesis submitted to the Faculty of the Graduate School,
Marquette University,
in Partial Fulfillment of the Requirements for
the Degree of Master of Science

Milwaukee, Wisconsin

December 2013

ABSTRACT
MPEER: A MOBILE HEALTH APPROACH
TO MONITORING PTSD IN VETERANS

Casey J. O'Brien, B.S.

Marquette University, 2013

More than 2.2 million US service members have seen deployment to Iraq and Afghanistan over the past decade. As the number of veterans returning home has increased, the need for new and innovative approaches to the variety and severity of mental health issues experienced after deployment remains a national priority. Affecting between 15-20% of the veteran population and largely treatment resistant, Post Traumatic Stress Disorder (PTSD) poses a challenging problem for the mental health community. Recent veteran related studies have suggested a paradigm shift in conceptualizing PTSD in terms of specific high-risk behaviors rather than traditional symptoms.

Young and technology savvy, many veteran populations are uniquely poised to embrace mobile health (mHealth) approaches to monitoring and addressing health related issues. In this thesis, we document the design and implementation of a smartphone-based system that coordinates the collection of data potentially relevant for monitoring high-risk behavior in veterans. We describe the details of an unobtrusive smartphone application for the Android platform that collects data from a variety of smartphone sensors and administers daily self-report questionnaires. Finally, we confirm system performance with data from student volunteers.

ACKNOWLEDGMENTS

Casey J. O'Brien, B.S.

I would like to thank my parents for their unflinching support and love. Their commitment to education, in all of its forms, has guided me through my studies over the years. Without Mr. Mark Murphy I would never have ended up at Marquette. I would like to thank him for taking me to visit the campus one cold winter's day back in December 2007. I would like to thank my advisor, Dr. Iqbal, for his guidance over the past five years—as an undergraduate and graduate student. A fierce advocate for his students, he has provided great support both in and out of the classroom. I would like to thank the other committee members. It has been a pleasure working with and getting to know Dr. Franco over the past year. I thank Dr. Madiraju for his valuable comments and suggestions. Finally, I would like to thank America's servicemen and servicewomen who put their lives on the line for the nation everyday.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

APA	American Psychological Association
API	Application Programming Interface
CTSI	Clinical & Translational Science Institute
DSM	*Diagnostic and Statistical Manual of Mental Disorders*
EC2	Elastic Compute Cloud
EMA	Ecological Momentary Assessment
HTTPS	Hypertext Transport Protocol Secure
IDE	Integrated Development Environment
IRB	Institutional Review Board
JSON	JavaScript Object Notation
LAMP	Linux, Apache, MySQL, PHP
OEF	Operation Enduring Freedom
OIF	Operation Iraqi Freedom
OND	Operation New Dawn
PE	Prolonged Exposure
PSTD	Posttraumatic Stress Disorder
REST	Representational State Transfer
SDK	Software Development Kit
TBI	Traumatic Brain Injury
UUID	Universally Unique Device Identifier
VA	Veterans Administration

CHAPTER 1: INTRODUCTION

With the recent war in Iraq and the continuing war in Afghanistan, the number of returning veterans continues to increase. More than 2.2 million service members have seen deployment to the Iraq and Afghanistan theaters over the past decade. Now that the wars are winding down, attention has turned to the medical issues with which veterans return. Projections of the cost of medical care for veterans reach as high as $1 trillion over the next 40 years [1]. The care for our veterans' health and wellbeing on their return demands new and innovative approaches to facilitating the transition back to civilian life. Meeting this demand requires us to attend to the unique characteristics of those who have served in recent wars and develop strategies specific to their experiences. Some have focused their attention on alarming rates of mental health issues, otherwise known as the so called "invisible wounds," which present a much more subtle and challenging problem for the medical community. A longitudinal study of returning veterans found that 20% of active soldiers and 42% of reserve component soldiers required mental health treatment after deployment to Iraq [2]. Among the variety of mental health issues that veterans face, the one perhaps most commonly associated with recent conflicts is posttraumatic stress disorder (PTSD). Affecting thousands of service members and largely treatment resistant, PTSD remains a significant national issue. New suggestions from Veterans Affairs (VA) researchers propose thinking about PTSD in terms of the high-risk behaviors often associated with the disorder rather than specific symptoms, which often remain chronic and resistant to treatment. This thesis presents and documents a mobile application (app), called mPeer, that collects sensor data from smartphones as well as self reported data to investigate the possibility of a technology-mediated intervention for PTSD in veterans.

Originally envisioned in a grant application to the Clinical and Translational Science Institute of Southeast Wisconsin (CTSI), the larger project of which this thesis forms a part proposes to develop an app that detects high risk behavior using existing smartphone technology. Drawing on an transdisciplinary team from academia with the Medical College of Wisconsin and Marquette University, community partners with DryHootch of America, and government with the Milwaukee Veterans Administration (VA), the pilot grant provides most of the necessary resources and vision to begin the process of realizing this goal.

Mobile technology applications in health care, concisely referred to as mHealth, continue to garner attention in both academic and industry settings. A recent paper by the Brookings Institute estimates that mHealth monitoring technology has the potential to save nearly $200 billion over the next 25 years [3]. With the ever-increasing onboard processing power, sensor arrays, and inter-device connectivity options, smartphones are especially poised to facilitate mHealth objectives. Despite being still in its relative infancy as a proper discipline, mHealth technologies have begun to appear in the VA mental health area. Recent apps from the National Center for Telemedicine & Telehealth such as PTSD Coach and PE Coach underscore the commitment from government to explore mobile-based approaches to reaching veterans. While these apps represent substantial efforts to bring mobile technology to bear on mental health outreach, they fail to exploit the true capabilities of smartphones to mediate mental health interventions, as they tend to focus on merely providing and organizing information in a mobile format. Using the rich sensor data available on smartphones to make inferences about and interact with users represents the next iteration of mHealth technology. It is precisely this next iteration that this thesis addresses.

By nature, mHealth application development teams are highly interdisciplinary. Drawing on established research traditions in modern medicine and technical expertise of computer science and engineering, mobile health requires understanding, as best one can, the relevant literature that supports a project. Broadly speaking, the supporting literature domains for this thesis include research and major works on PTSD, behavioral risk, and mobile health. And while the application envisioned in this thesis exists at the intersection of these three domains, each has individual contributions and perspectives that are useful to consider.

The application presented in this thesis exists in the context of a peer mentoring relationship. Our community partner, DryHootch of America, has an established program of organizing peer mentoring relationships between returning military veterans and peer mentors. At its most basic level, the mobile app strives to improve the kind of objective behavioral data available to inform this relationship as well as allow peer mentors to scale their operations to handle more veterans. The app's antecedent, called iPeer, has begun the process of incorporating smartphone-based data collection, in the form of surveys, into the mentoring process. iPeer provides mobile applications for collecting veteran survey responses, administered at contextually relevant times, and viewing those responses in both aggregated and specific forms. The mPeer app works to fit within the framework already developed in iPeer but brings different kinds of data to bear on the monitoring of veteran mental health and high risk behavior.

The nature of the risk we are considering is markedly different from the majority of other kinds considered in the literature. As Dr. Zeno Franco put it, "we are working at the *edge* of risk." We know that the veterans who will be recruited for the pilot study are already at "high risk" in a number of ways. Some will have a history at the Milwaukee

County Drug Court, others at mental health clinics. The challenge posed is not to identify risk based on population statistics but rather to predict when an individual is on a trajectory towards engaging in high risk behavior. This challenge, we suggest, requires understanding an individual's behavior and watching for changes in his baseline. For example, a veteran struggling with alcohol might drink at a local bar every night. Detecting this singular piece of information, while interesting, does not reveal much about his future high risk behavior. However, if his drinking habits change and he, say, starts drinking earlier in the day, then we have evidence of a behavior change that could be material for his peer mentor. On the other hand, if we detect a positive change, such as his frequency of bar visits decreases, then capturing this objective behavioral change would be useful in documenting the veteran's pathway to managing his PTSD.

The previous example raises the question of what kinds of data would be necessary to detect, say, changes in drinking habits using the sensor and contextual data of a smartphone. At a basic level, we would need to be able to detect when an individual is drinking. Activity detection using smartphone accelerometers has been successful for discriminating such activities as running from walking, or riding in a car from riding a bicycle. Due to the wealth of sensor data available on today's smartphones, we must prioritize those which discriminate activities most effectively. To detect when an individual is drinking, one can imagine using the GPS (Global Positioning System) traces to tell if a veteran is at a bar. Thus, we can introduce a propositional logic to compose smaller contextual pieces of information together to infer behavior. For this example, we have propositions like "in a bar" (from the GPS and geocoding service) and "sitting down" (from the accelerometer), which taken together can indicate that a user is drinking. It should be noted that these conclusions are clearly not always correct. Inferring behavior from smartphones continues to evolve. However, in our case, with the kind of individuals recruited for participation in this larger project, the truth value of the propositions themselves can be important for a peer mentoring relationship. Merely "being in a bar" becomes relevant for the high-risk returning veteran population. One of the goals of the original proposal is to build an *a priori* algorithm before the application becomes available to veterans. The propositional logic model allows one to compose a language of high-risk behavior from a conceptually driven model rather than having a complex training process based on samples of high-risk behavior, which hopefully will be rare.

One criticism that has been offered anecdotally to the overall approach to this kind of data collection is the potential lack of willingness of participants to join given the sensitive nature of the data captured. Veteran populations, especially those with PTSD, have fervent concerns with providing personal information. A system such as ours, which unobtrusively gathers data about a veteran, could be perceived as threatening. An intake supervisor shared in conversation that many veterans whom she interviews describe a persistent need to "defend their position." This phrase can take on a variety of different interpretations, the most overt of which describes a need to protect their location information with respect to others. The use of constant GPS monitoring clearly presents a tension with respect to this need. The design and development of this mobile app contemplates and attends to the security and privacy concerns of veterans such as these. We use industry standard encryption to secure the communication channels between mobile devices and the larger system. We also intend to implement geo-obfuscation techniques to prevent the exact location of veterans being disclosed. For the example discussed above, we are not interested in the precise geo-coordinates of the veteran at a bar. We are merely interested in the fact *that* a veteran is at a bar. The question becomes then, how can we obtain that information without knowing the exact location of the veteran? We propose a separation of concerns where the mobile device determines that it is at *a bar* and provides only that information to the system. Specific details that are not essential for determining the truth value of the proposition, such as which bar, are not provided. Our approach is to acknowledge that data which we do not collect cannot ever be compromised or leaked in the future. We also recognize that the issues of privacy and the willingness of participants to use the system will not solely be resolved by technical means. There is a social component as well that requires building trust between the diverse parties involved: system developers, medical practitioners, veterans, and peer mentors. The trust already built by our community partner, DryHootch, begins a dialogue that we need and will continue to have in order to respond to the human elements of projects such as ours.

The main contributions of this thesis are threefold: first, we introduce the design of a system that coordinates the collection of data relevant to monitoring high risk behavior in veterans; second, we describe the implementation of a mobile smartphone app for Android that gathers sensor data and uploads these data to a cloud server; third, we present and analyze the data collected for five student participants over one week that demonstrates the functionality and use of the app.

The remainder of the thesis has a structure as follows. Chapter 2 presents the necessary background about the mPeer project. In this chapter, we discuss PTSD, mobile health, and behavioral risk. Chapter 3 identifies and organizes the related literatures that inform and support the thesis. Chapter 4 describes the design of the overall system architecture in which the mPeer app for Android functions within the context of a peer mentoring relationship. Chapter 5 documents the implementation of the Android app and cloud server software. Chapter 6 outlines the data collection procedures, the data collected, and a preliminary analysis of the data. Finally, chapter 7 concludes the thesis and points towards future work.

CHAPTER 2: BACKGROUND

In August 2011 in a speech at the Annual Conference of the American Legion, President Barack Obama called posttraumatic stress disorder (PTSD) a “signature wound” of the recent wars in Iraq and Afghanistan [4]. Others have referred to PTSD and related mental health conditions as “invisible wounds.”

The United States has been involved in two major military conflicts spanning more than the last decade. The war in Afghanistan, officially known as Operating Enduring Freedom (OEF), began on October 7, 2001, under the Bush Administration. The war in Iraq, officially known as Operation Iraqi Freedom (OIF), began on March 20, 2003, and ostensibly continues to this day under the new name Operation New Dawn (OND). On September 1, 2010, President Obama marked the reduction of US forces in Iraq with a change in the war’s name. While the distinction between the operations might seem pedantic, the different names appear on official military documents and much of the medical and epidemiological literature surrounding the conflicts. Figure 2.1 contains a graphical timeline of the two conflicts. Since 2001, more than 2.2 million military service members have been deployed to Iraq and Afghanistan [5].

The nature of the recent wars in Iraq and Afghanistan differ in large measure than previous major conflicts in which the United States has been involved, such as the world wars, Korea, and Vietnam. Whereas previous major conflicts have involved drafts, the forces that have composed the Iraq and Afghanistan conflicts draw on an entirely volunteer military. Advances in medical treatment and technology have led to a reduced casualty rate. More people who are gravely injured are able to be saved but often return with dramatically different living habits due to bodily injuries or psychological scars. The

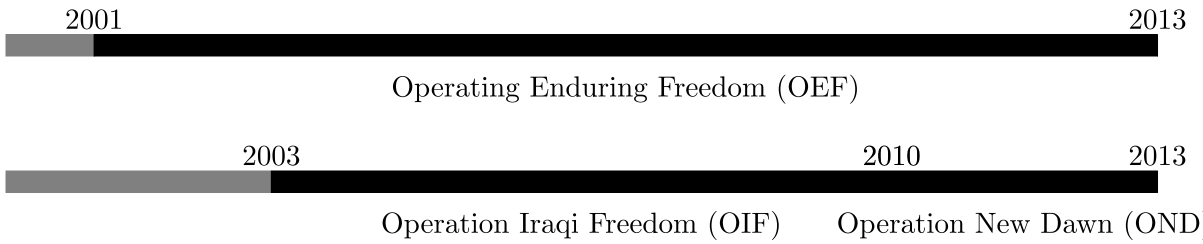

Figure 2.1: Timeline of Recent US Wars

use of IEDs (improvised explosive devices) by enemy forces subject service men and women to great danger, often unanticipated and unknown until detonation. These devices have been implicated in the high rate of TBI (traumatic brain injury) and PTSD. Service members are also deploying more frequently and for longer periods than in previous wars. When they return to their communities, they often do not meet supportive structures that facilitate their transition back to civilian life. Being exposed to such traumatic events, veterans are at greater risk for suicide, bodily harm, substance abuse, and other mental health disorders [6].

2.1 Prevalence of PTSD

Establishing the prevalence of PTSD in the military remains a difficult task. In 2008, the RAND Center for Military Health Policy Research published a substantial manuscript synthesizing the research on PTSD and suggesting paths forward for addressing the unique needs of the military community [7]. Of the 22 studies analyzed, the majority of which estimate PTSD in OEF and OIF service members, prevalence estimates of PTSD range from 5-15%. Each study used slightly different procedures, screening instruments, and sampling techniques. One commonly cited 2007 study of 103,788 veterans who left the service and sought care from the VA system used ICD-9-CM (*International Classification of Diseases, Ninth Revision, Clinical Modification*) codes from patient medical records to reach a PSTD prevalence rate of 13% [8]. A 2008 population-based survey administered by the RAND corporation itself of previously deployed service members resulted in a rate of probable PTSD of 13.8% [7]. One might wonder how the rate of PTSD compares to that of the general population. Data from the 2001-2003 National Comorbidity Survey Replication (NCS-R) of adult Americans using DSM-IV criteria was used to estimate that the lifetime prevalence of PTSD to be 6.8% [9]. Using data from the same survey, the 12-month prevalence PTSD was estimated to be 3.5% [10]. From these numbers, it is clear that the rates of PTSD are substantially higher than among the general US population. Because of these alarming rates, the host of troubling symptoms, and consequences of the disorder, PTSD has garnered much popular attention over the past few years.

2.2 Comorbidity of PTSD

PTSD often occurs comorbidly with other mental health disorders. In population studies, it has been suggested that people with PTSD have on average 2.7 other mental health diagnoses [11]. The recently published DSM-5 says that "individuals with PTSD are 80% more likely than those without PTSD to have symptoms that meet diagnostic criteria for at least one other mental disorder" [12]. Treating individuals with only PTSD remains challenging enough, but treating individuals with PTSD that is comorbid with other disorders becomes even more difficult. The RAND study mentioned earlier finds that nearly two thirds of military personnel surveyed had met criteria for probable depression [7]. Evidence shows that PTSD occurs comorbidly with traumatic brain injury (TBI) [7]. Anxiety, alcohol and substance abuse, and affective disorders have been identified as comorbid with PTSD as well. Recognizing that PTSD occurs quite often with other psychological disorders becomes important to understanding the context of those veterans with PTSD.

2.3 Mobile Health: mHealth

Originally called “Unwired E-Med,” mHealth (also, but not commonly written “M-Health”) has historical roots in both telemedicine and e-health [13]. While essentially defined in 2000 and officially called “M-Health” by Robert Istepanian in 2003 [14], the literature did not coalesce around the term mHealth until around 2004 when *IEEE Transactions on Information Technology in Biomedicine* published a guest editorial on mHealth [15] and 2005 when many of the same authors released a book on mHealth in the Springer published *Topics in Biomedical Engineering* series [16]. Because of its rapidly changing nature, mHealth has gone through a number of semi-canonical definitions. Table 2.1 contains a list of these definitions. The mHealth Alliance [17] and the related annual mHealth Summit are specific forums for discussing, collaborating, and presenting new trends in the field. Founded in 2009 with corporate and nonprofit support, the mHealth Alliance advocates the integration of mHealth technology into existing medical environments as well as the release of novel applications.

Author	**Date**	**Definition**
Istepanian, et al. [15]	2004	“mobile computing, medical sensor, and communications technologies for health-care”
Istepanian, et al. [16]	2005	“emerging mobile communications and network technologies for health-care systems”
mHealth Alliance [17]	2009	“medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, tablets, personal digital assistants (PDAs), and other wireless devices”

Table 2.1: mHealth definitions

The use of mHealth challenges many of the established norms in medicine. While it offers great potential to transform the delivery and access of healthcare, left unprincipled, it has the potential to transgress the Hippocratic oath[1].

2.4 Dryhootch Community Partner

Founded in 2008, Dryhootch is a Milwaukee-based community organization with a mission to provide help to veterans making the transition from deployment back home [18]. Their slogan, "helping the veteran and their families who survived the war, survive the peace," underscores their understanding of the challenges that face returning veterans. Their name comes from the the term "hootch," coined and popularized during the Vietnam war, which came to mean a safe place to stay in a combat zone. Acknowledging the difficulties many veterans have with alcohol abuse, their use of the word "dry" comes from the colloquial term for alcohol-free.

As part of their mission, Dryhootch organizes and coordinates the formation of mentor/mentee relationships among veterans. With two physical establishments—one next to the VA hospital in Milwaukee, Dryhootch works to facilitate the transition of veterans back into the community. The ultimate goal of this project, albeit several iterations down the line, is to help provide objective behavioral data to mentors about their veteran mentees. By providing them clearly analyzed data, they can not only better serve their mentees but also scale up to handle more mentees at a time. The veteran mentors are not licensed clinical psychologists and should not be expected to provide the same level of care. Our vision is to provide mentors with the tools to enhance their ability to oversee multiple returning veterans.

[1] Physicians typically swear to uphold the Hippocratic Oath, which, according to the more commonly associated adage, is to "first, do no harm." However, the text does not contain those exact words. Among its many lines, it reads "I will apply dietetic measures for the benefit of the sick according to my ability and judgment; I will keep them from harm and injustice." As mHealth continues to expand as a decision support system (and in some cases a decision making system), it would do one well to remember this oath and perhaps have computer scientists take it too.

2.5 CTSI Grant

The work in this thesis forms an initial part of a pilot award grant from CTSI (Clinical & Translational Science Institute) of Southeast Wisconsin to detect high risk behaviors using smartphone technology. Using both smartphone sensor data and self-reported ecological momentary assessments (EMAs), the grant proposes to obtain both an exploratory and confirmatory data set. Forty OEF/OIF veterans will be recruited through a variety of avenues, including the Milwaukee County Drug Court, Dryhootch, and referrals from mental health care facilities, who show a propensity for high risk behavior. Having been provided a smartphone capable of running the behavior detection application, these veterans will receive \$150 in gift cards, disbursed in \$50 increments, over the course of the 16 week pilot study. This project is truly transdisciplinary in that it involves a variety of stakeholders from the community, academia, and medicine. As valuable as the actual data being collected as part of the study is the infrastructure built to support such an endeavor and the lessons learned in doing so.

2.6 Relationship to iPeer

An almost identical group of investigators as those included on the CTSI grant have another similar project called iPeer, which can be thought of as this project's antecedent. iPeer is a mobile app for Android that administers a variety of questionnaires to veterans throughout the day and presents their responses to their mentors through a dashboard interface (also on a mobile device). The difference between iPeer and this project is that here we are also collecting data using the sensors on the smartphone in addition to the self-reported data from survey instruments.

Indeed this project can learn from the experience in developing iPeer. As the iPeer system deploys and receives feedback from veterans and mentors, one can begin to answer questions like, What are the most effective survey instruments to administer? Since iPeer will be deployed before mPeer, learning from the developers' experience will be important as the Ubicomp Lab begins to build the knowledge and capacity for developing and handling these kinds of systems.

CHAPTER 3: RELATED WORK

When considering the literature domains that support an mHealth approach to monitoring veteran mental health, we suggest three general areas: research into PTSD, literature about behavioral risk, and current literature on mobile health technology. The Venn diagram in Figure 3.1 shows a basic heuristic for visualizing the space of literature involved. Each area itself has a rich, established literature in its own right. What we are mostly interested in here is where these domains overlap. This chapter will demonstrate that whereas there are works that already exist within the intersection of some of the domains, there are very few that exist in the intersection of all three.

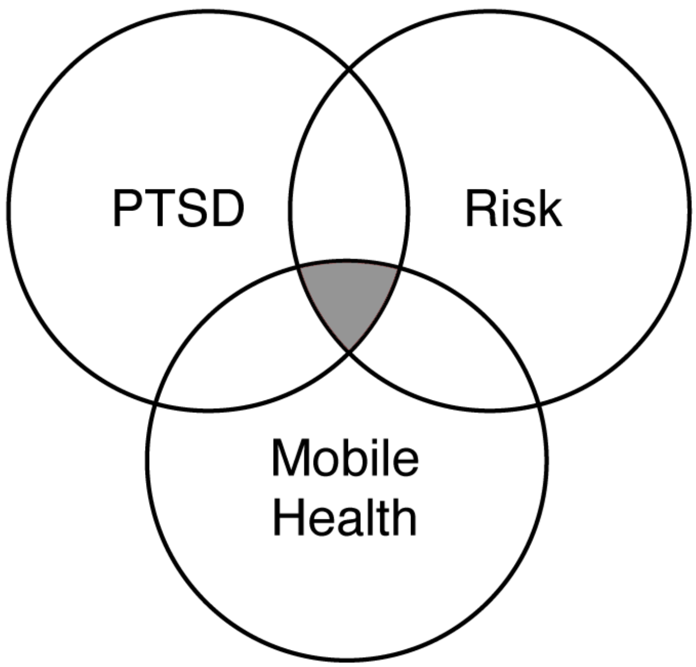

Figure 3.1: A Venn diagram of the supporting literature

3.1 The Intersection of PTSD and Mobile Health

While very few works exists at the intersection of PTSD and mobile health, there are a few. Almost all the works in this area belong exclusively within the US Department of Defense and the US Department of Veterans Affairs. The major players are the National Center for Telehealth and Technology and the Department of Veterans Affairs (VA), particularly the VA campus in Palo Alto.

A component center of the Defense Centers of Excellence for Psychological Health & Traumatic Brain Injury (DCoE) at the US Department of Defense, the National Center for Telehealth and Technology (T2 Health) was founded in 2008 with a mission “to lead the development of telehealth and technology solutions for psychological health and traumatic brain injury of the Nation’s Warriors, Veterans, and their Families” [19]. T2 Health currently has 11 mobile applications, almost all for both Android and iPhone platforms, related to their mission. Among applications for breathing, relaxation, and traumatic brain injury are two applications related to PTSD: PTSD Coach and PE Coach.

A mobile application intended to help veterans with symptoms, PTSD Coach [20] was developed by the National Center for PTSD in collaboration with the National Center for Telehealth & Technology. With four major features–self-assessment, management of symptoms, finding support, and education, PTSD Coach is billed as an application for the “self-management of Posttraumatic stress.” The questionnaire administered in the app is the PTSD Checklist (PCL), a commonly used screening instrument for PTSD [21]. The application serves as more of an information provider about PTSD than a treatment assistant like PE Coach. Veterans can also track their level of stress on a scale of 0-10 with a visual thermometer. There are a variety of stress reducing exercises that the application guides the user through. There are many similar mobile applications that have been developed by coalition governments in Canada and Australia. PTSD Coach received a 4.5/5.0 score out of 74 ratings on the Apple AppStore (most recent version 1.0.1 April 13, 2011) and a 3.9/5.0 score out of 181 ratings on the Android Play Store (most recent version 1.0 June 2, 2013).

Developed by the National Center for Telehealth & Technology with collaborators from the National Center for PTSD and The Center for Deployment Psychology, PE Coach [22] is a mobile application that supports Prolonged Exposure (PE) [23] psychotherapy sessions. Focusing on the elements of PE clinical practice, the application tracks session tasks, audio recordings of sessions, educational material, and patient homework assignments. With respect to data security, PE Coach allows the patient to specify an application specific password to protect his data. Other than that, the application provides no other security or privacy protections and notes that HIPPA rules only apply when data are shared manually with healthcare providers. As of now, there is no facility for sharing data electronically. The primary feature of this application is the ability to record therapy sessions, play them back later, and provide the patient with homework exercises as he reexperiences previous sessions. PE Coach has both Android and iPhone versions. PE Coach received a 4.5/5.0 score out of 10 ratings on the Apple AppStore (most recent version 1.3 July 6, 2013) and a 3.9/5.0 rating out of 14 ratings on the Android Play Store (most recent version 1.3 July 6, 2013).

Developed by Mobile Roadie for the Hope for One nonprofit organization, PTSD Support for Veterans is a mobile application for veterans and their families to learn about and understand PTSD. Using a tabbed interface, the application provides the following sections: news, videos, podcasts, links, fan wall, and mailing list. Drawing on both medical professionals and individual veterans with PTSD, the application attempts to provide a variety of informational materials and suggestions about dealing with PTSD. PTSD Support for Veterans received a 3.5/5.0 score out of 13 ratings on the Apple AppStore (most recent version 4.6 October 31, 2011) and a 4.3/5.0 out of 48 ratings on the Android Play Store (most recent version 4.7.0.1 July 23, 2013).

A partnership between Dr. Steven Woodward of the Palo Alto VA Heath Care System and Fujitsu Laboratories of America, a research project entitled "Enhancing Emotion Regulation During Driving in OEF/OIF Veterans" exists that attempts to study the driving habits of PTSD veterans from recent deployments [24]. Researchers instrumented a car with sensors on the steering wheel, brake pedal, and gas pedal. While driving, a sensor system also monitors the veteran's breathing and heart rate. Researchers also recorded any significant driving incidents manually on an iPhone while in the car. A a small in-car web server collects all these data via Bluetooth. Veterans receive three in-car treatment sessions and an appointment with a psychologist. While many newspaper articles exist touting this project from both the Palo Alto VA and their corporate sponsor Fujitsu [25], Dr. Woodward has yet to publish anything in the literature about it. An entry in the registry of clinical trials (NCT01336764) states that the estimated completion data was April 2012 but does not contain any study results [24].

Table 3.1 compares all four mobile applications mentioned above presented in the order they appear in this text. The date column lists the date that the application first appeared on mobile distribution sites (like the Apple AppStore or the Android Play Store) or in popular literature.

PTSD patients reexperience traumatic events when they encounter triggers. The first documented use of a virtual reality system appeared in the *Journal of Traumatic Stress* in 1999 [26], which presented a case study of a 50-year-old Vietnam veteran

Application	Date	Questionnaire	Sensors	Analytics
PTSD Coach	2011	PCL	-	-
PE Coach	2013	PE	-	-
PTSD Support	2011	-	-	-
Enhancing Emotion	2011	-	Many	-

Table 3.1: Comparison of Mobile Applications

meeting DSM-IV criteria for PTSD. Some have argued in the literature that among the different types of cognitive behavioral therapy (CBT), exposure therapy shows the most evidence for use in PTSD cases. [27] At the core of exposure therapy lies the intuition, backed by several studies, that traumatic events must be processed emotionally, something that cannot happen when the event occurs. By exposing a PTSD veteran to a virtual environment similar to that of combat, he can begin to work on processing the event in a more healthful way.

3.2 PTSD

Often referred to as the bible of mental health disorders, *The Diagnostic and Statistical Manual of Mental Disorders* codifies the language and classification of mental health and diagnostic criteria for mental health disorders. Earlier in 2013 the American Psychological Association (APA) released the DSM-5 (fifth edition), which replaces the DSM-IV published in 1994 [12]. In the latest edition, the APA has made some changes to their description of and diagnostic criteria for PTSD and includes PTSD in a new chapter on "Trauma and Stress or Related Disorders." DSM-5 focuses on defining a "traumatic event" and does not discuss an individual person's response to an event. It also defines four diagnostic clusters: reexperiencing, avoidance, negative cognitions and mood, and arousal. DSM-5 requires that disturbances be present for more than one month to qualify as a recognized disorder. A change from the previous edition, DSM-5 also acknowledges the behavioral symptoms of PTSD.

Incidentally, the current literature from APA surrounding the release of DSM-5 addresses the concern of some members of the military community regarding calling PTSD a “disorder.” Some have expressed the notion that calling it a disorder stigmatizes it in an unhealthy way. While APA recognizes this as a potential issue, it decided not to change the name for the fifth edition.

In terms of the treatment of PTSD symptoms, there are a variety of effective treatments. With theoretical roots back to the 1940s [28], prolonged exposure therapy (PE therapy) was developed by noted psychologist Edna Foa of the University of Pennsylvania to treat PTSD in rape victims [29]. Currently, it serves as one of the two evidence-based treatment therapies for PTSD endorsed and supported by the VA Office of Mental Health Services. A 2013 study of the implementation of PE therapy across geographically diverse VA facilities observed a clinically significant reduction in PTSD symptoms and the proportion of veterans screening positive for PTSD [30]. With this compelling evidence for the effectiveness of PE as a treatment for PTSD and the support for training VA therapists in PE, it makes sense that the National Center for Telehealth & Technology developed PE Coach [22] to facilitate PE therapy sessions.

3.3 Mobile Health: mHealth

As discussed in chapter 2, mobile health (mHealth) has only formally existed in the literature since 2000. As mobile technology continues to have improved over the last decade or so, the opportunities of mobile health to be transformative in the healthcare field have expanded. A recent workshop in 2011 organized by the National Institutes of Health (NIH) on mHealth stated, “rigorous research is needed that examines the potential, as well as the challenges, of using mobile technologies to improve health outcomes...mHealth technologies may detract from, rather than contribute to, what is needed for true overall health improvement" [31]. This workshop identified the need to establish reliability and validity in mHealth and suggested research design strategies for evaluating the efficacy of mHealth interventions. mHealth will surely continue to expand as more players see the potential public health opportunities and associated money to be made.

3.3.1 EMA: Ecological Momentary Assessment

First formally defined and explained in 1994 by Stone and Schiffman [32], Ecological Momentary Assessment (EMA) describes "methods using repeated collection of real-time data on subjects' behavior and experience in their natural environments" [33]. EMA overcomes the limitations of structured, controlled environments such as laboratories or clinics. By administering data collection protocols in a subject's natural environment at a critically defined time, one can gather a great deal of information otherwise unavailable or biased in some way. Successfully applied to several smoking cessation studies, EMA remains a common way of collecting behavioral data. Many tests and procedures in clinical psychology require the patient to report on, say, his mood retrospectively. EMA allows one to collect information on mood in the field. This is not to say that EMA is perfect; there are many research questions for which EMA will not work.

The growth of mobile phones provides a unique new method for administering EMAs. Many people carry their phones on their person during the day. The mobile ecosystem presents a number of possibilities to incentivize participation and monitor participant engagement with the assessments. The success or failure of EMAs largely depends on how compliant subjects are to the protocols of the assessment. A 2010 study in Switzerland involved calling participants cellphones to collect data related to mood and tracked compliance features over the one-week length of the study [34]. The study had a computer call participants six times per day in 2-hour windows and administer 12 questions on momentary mood. The analysis of compliance and factors affecting compliance appeared in a subsequent article [35]. Defining compliance as answering the phone call from the computer during a given window, the authors collected timing characteristics of calls such as the day of the week and the day into the study. The analysis found that mean compliance was 74% overall and never went below 60%. Interestingly, across day analysis revealed that Monday showed the lowest compliance after which it steadily rose until Thursday. Also, compliance over the first four days remains "similar," then drops off to around 67%. Intra-day analysis showed that compliance was lowest in the morning and highest in the late afternoon.

There are a few mobile apps either available now or in development specifically for collecting EMA data. The ilumivu software company offers a system with a variety of modules to collect and analyze EMA data [36]. Their iPhone app is called mEMA and is available on the AppStore but requires an online account with the company to configure assessments. The most recent update, version 1.4, came out on July 16, 2013, and does not have any reviews. Pricing for 1000 active participants requires an annual license that costs $3,000. On their website they identify four autism-related projects that use the illumivu system; although the extent to which these projects make use of all the claimed features of the ilumivu system is unclear. Their specific EMA configuration markets to behavioral researchers who want to collect EMA surveys, gather data from participants with on-phone sensors and external biosensors, and view their the collected data in an analytics module. The illumivu system does not allow for data to be collected outside of assessment windows.

Created by a team of psychology researchers at Indiana Wesleyan University, the iHabit app exclusively for iOS allows customers to create and administer questionnaires to participants [37]. Described as an EMA platform, iHabit comes in standard, premium, and custom versions, with the standard version starting at $2,000 for up to 100 respondents. Participant responses are available to the customer over email. The most recent version 1.12 was released August 21, 2012. Their website mentions one project in which their software has been used to study the habits of "Christian exemplars," individuals who are model Christians according to their community.

A spin-off from a German University group, movisensXS is marketed as an experience sampling method app exclusively for Android, which is currently in beta testing. Available in different versions with varying capabilities, a 100 person study costs 3,000 euros (nearly $4,000). One interesting feature is their interface for designing questionnaires, which includes an online graphical editor.

An open-source tool for the Android platform, PACO (Personal Analytics Companion) provides the facility for developing personal or experimental studies [38]. PACO supports both experiential sampling or fixed sampling schedules. There is no support for sampling from mobile phone sensors in addition to questionnaires. It is unclear when the application will be available for researchers to use.

For a good list of EMA applications for mobile devices, including those that are not specifically designed for EMA, consult [39].

3.4 High-Risk Behavior

Studies indicate that PTSD symptoms are largely resistant to both inpatient and outpatient treatment [40, 41]. Hartl, et al., from 2005 suggest that "relapse in this population might better be defined in terms of high-risk behaviors rather than symptom reoccurrence or exacerbation" [42]. Their work looks at 630 male inpatients at a VA residential program for PTSD in Palo Alto, CA, and tries to predict those patients that

Behavior	References
Speeding	[43], [12]
Binge drinking[1]	[43], [44]
Drunk driving	[43], [12]
Physical fighting	[44]
Attempting suicide	[42], [12]
Violence	[42]
Misuse alcohol	[42],[12]
Misuse hard drugs	[42]
Risk/thrill seeking	[43]
Less sociability	[43], [12]
Hypervigilance	[12]
Angry outbursts	[12]
Self injury	[12]

Table 3.2: High-risk behaviors associated with PTSD

are at greatest risk of relapse, using this new definition.

Recently, there has been a growing body of literature that attempts to define the specific high-risk behaviors of interest and how to predict those individuals at greatest risk of future high-risk behavior. This goal is perhaps too ambitious for now; researchers tend of hedge their presentation of their work as *factors* associated with PTSD. For the purposes of our project, we are not keenly interested the statistical minutiae of things such as "proving" causation. We are interested in gathering together specific risky behaviors associated, in some meaningful sense of the word, with PTSD. The DSM-5, with its new emphasis on behavioral features of PTSD, provides some examples of risky behaviors related to PTSD as well.

Table 3.2 contains specific high risk behaviors and references that document those behaviors as they relate to PTSD. Some of these behaviors are inherently risky to a veteran's person (e.g., misuse of hard drugs, drunk driving, attempting suicide) while others are risky in the degree to which they are present and what that might mean for the veteran (e.g., less sociability, hypervigilance).

3.5 Technical Considerations

There are some technical considerations that draw on established literatures as well. In this section, we look at some of the technical issues around the frequency and resolution of sampling required for such a project. Additionally, we examine the use of unique device identifiers and the problems presented with respect to security and privacy.

3.5.1 Sampling Frequency

Current embedded MEMS (micro-electoro-mechanical systems) sensors found in smartphones have the capability to deliver hundreds of samples per second. The MPU-6050 Six-Axis MEMS chip, the integrated gyroscope and accelerometer used in the Google Nexus 4 phone, has a variety of acceleration ranges up to $\pm 16\ g$ and can produce samples at 1 kHz or higher if configured to do so [45]. However, for a variety of reasons the effective smartphone sensing frequencies are an order of magnitude less. Operating systems priorities, lower power requirements, and practical application requirements dictate a slower sampling frequency.

While their specific application measures the work and efficiency involved in human activities, Sun and Hill found from Fast Fourier Transform (FFT) analysis that the majority of human activities detectable by force-related instruments have frequency components between 0.3 and 3.5 Hz, with very few above 10 Hz [46]. A conference paper from Junker, et al., briefly examined the effect of sampling frequency and bit resolution on context recognition classification problems [47]. They found that improvement in classification based on a sliding window mean, variance, and root-mean-squared features does not improve substantially at frequencies higher than 20 Hz and resolution greater than 2 bits. More recent concerns in the literature about sampling frequency seem to be illusive—probably attributable to the ability to collect and process high frequency data with modern smartphones.

3.5.2 UUIDs

Recent attention has been drawn to the ways in which Universally Unique Identifiers (UUIDs) can be used to identify a mobile phone and more specifically track a mobile phone's user. In 2012, a hacking group affiliated with the "Anonymous" organization posted one million UUIDs from a variety of iOS devices online [48]. While the identifiers by themselves are relatively innocuous, the tracking of these identifiers can reveal a wealth of information about a device's user. Because UUIDs for smartphone devices are unchangeable, their collection by application developers poses privacy concerns. The blog TechCrunch reported that Apple had begun rejecting apps that access these identifiers in early 2012 because of privacy issues [49]. Some applications have turned to generating their own unique identifiers; however, these approaches raise their own questions because of their lack of persistence. For example, if the user uninstalls and then reinstalls an app, the identifier would be lost.

CHAPTER 4: SYSTEM ARCHITECTURE

In this chapter, we present the design of the overall system architecture of mPeer. The first part discusses the basic system architecture developed for this thesis while the second part describes the eventual mPeer system as it related to peer mentorship. Three main design principles governed the design and development of the system architecture. These principles influenced both high-level and low-level design decisions.

1. Unobtrusiveness. The monitoring system should be as unobtrusive as possible. Veterans should not have to worry about such actions as starting or stopping the application or uploading data records.

2. Ease-of-use. For the components of the application that require veteran input, the interface should be as intuitive and easy-to-use as possible.

3. Security and privacy. Collected data should be secure across all devices–on the phone, on the server, and across all communication channels. Safeguards should be in place to ensure that veteran privacy is ensured. It should be difficult, in some sense, to map a data record back to the veteran who submitted it.

In order to meet our design principle of unobtrusiveness, the application must be able to handle a variety of operations on its own. Our goal with this mobile system implementation is to automate as much as possible. Sensor data are collected and uploaded automatically without user intervention. The application should know how often to administer self report questionnaires, following up throughout the day if necessary. We want to ensure that the application does not become annoying while at the same time obtaining the data required.

The interfaces designed for this project are simple and straightforward. They conform to the standard Android interface guidelines. Each Activity, such as the self report activity, represents a single conceptual act.

From the device, we are collecting data that are private. As such, we must ensure that data are transported and stored securely. There are two kind of stakeholders that one can envision here. First, there is the mobile user who takes his phone with him wherever he goes. This user expects should he lose his phone, personal data from the application are not accessible to strangers. Second, there is the veteran user who wants to ensure that his data are not accessible by the VA or other government agencies [50]. The level of privacy expected from the veteran user differs in many ways from the mobile user.

4.1 Overview

We can consider the system to follow a standard smartphone-cloud architecture. The main actors in this system are the mobile devices and the cloud server. Figure 4.1 shows a graphical representation of the architecture. At the bottom of the figure are n smartphone devices that collect a variety of sensor and self-assessment data. They regularly communicate to the cloud server using REST (Representational State Transfer) over HTTPS (Hypertext Transport Protocol Secure). At the top of the figure lies the cloud server, which handles the storage, visualization, and analytics related to the data from the individual smartphones.

4.2 Data Structures

Before developing any data structures, one must consider the nature of the data being collected. Thinking about the data, we are collecting high density data from sensors on mobile phones. This categorization fits well regardless of whether we are dealing with accelerometer sensors (which can sample at high frequency) or light sensors (which sample

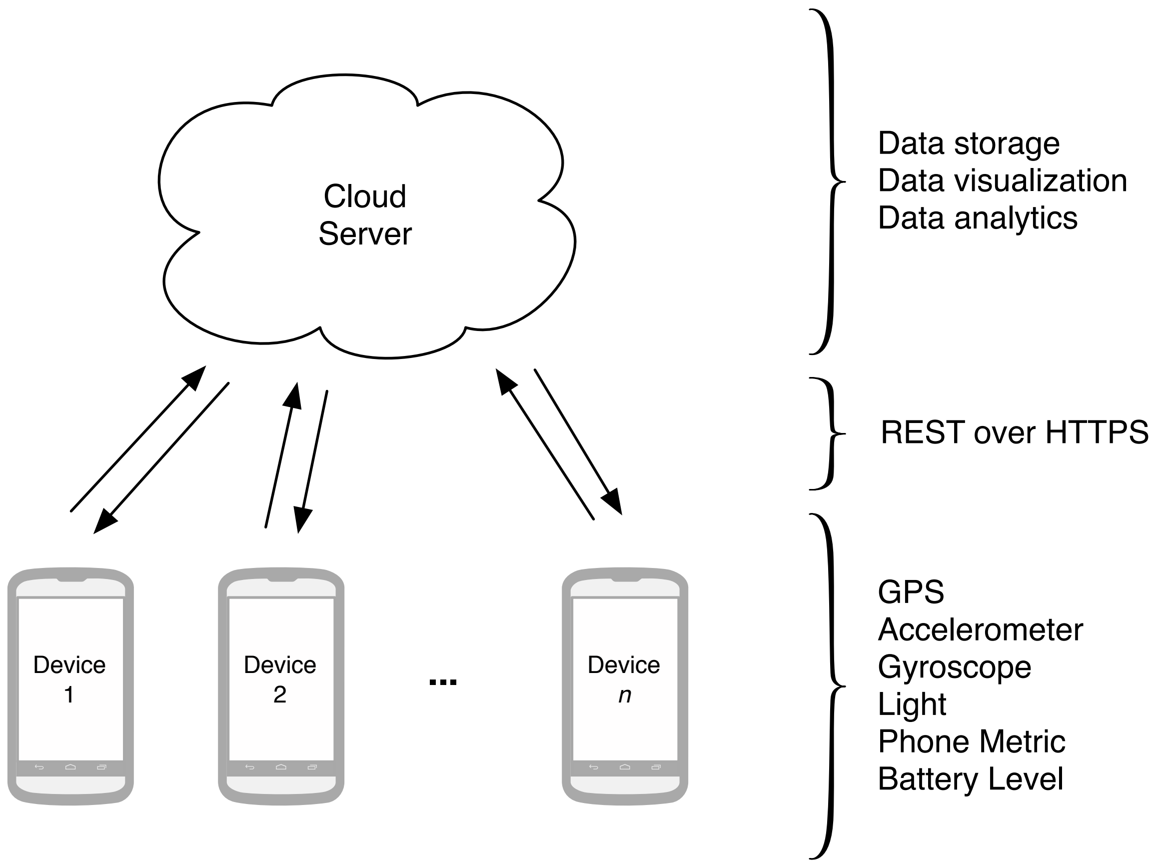

Figure 4.1: System architecture overview

at much lower frequency). For sensor data we are interested, in the timestamps of when the data were collected. These timestamps are often not as accurate as we would like due to time-sharing and other operating system features. However, we assume they are accurate for our purposes. For the exploratory application described in this thesis, we are interested in collecting all sensor data generated under the parameters described. While this goal becomes problematic in practice, we want to understand the raw data first before looking towards making analytical statements and inferences.

Bundling all the data and metadata we are interested in, the basic structure we used was a "record." On a mobile device, a record contains the following attributes:

identifier, type, value 1, value 2, value 3, assessment number, timestamp, event timestamp, and upload timestamp. This record structure is descriptive enough to accommodate all the kinds of data we are collecting, from a sensor sample to a response to a self-report question. Records are stored in an SQLite database on the phone before they are uploaded to the server when a WiFi connection becomes available. Once they are uploaded to the server, records contain slightly more information. In addition to those attributes named above, they contain a subject identifier and an upload identifier.

For structuring the communication of the records from the device to the server, we used JSON (JavaScript Object Notation). Less verbose than XML (Extensible Markup Language), JSON currently is the object notation of choice for communicating data in text-based formats.

4.3 Database Design

There are two databases involved in the system: one that resides on the user's phone and another in the cloud. While similar, the database in the cloud has some extra tables to keep track of certain accounting metrics of interest. The database on the phone runs SQLite and stores record entries as they are received from the sensors but before they are uploaded to the cloud database. Figure 4.2 shows a an extended entity relationship (EER) diagram for the cloud database. Not all attributes for the record entity have been presented in the diagram. Missing are: *Value1*, *Value2*, *EventTimestamp*, *UploadTimestamp*, *AssessmentNumber*. The SQLite database on the devices only contain a table *Record* with the following attributes: *Id*, *Timestamp*, *EventTimestamp*, *Type*, *Value1*, *Value2*, *Value3*, *AssessmentNumber*, *UploadTimestamp*. All the timestamps are stored as long integers in the standard Java date format (number of milliseconds since January 1, 1970), with the exception of *EventTimestamp* which records the number of nanoseconds since January 1, 1970.

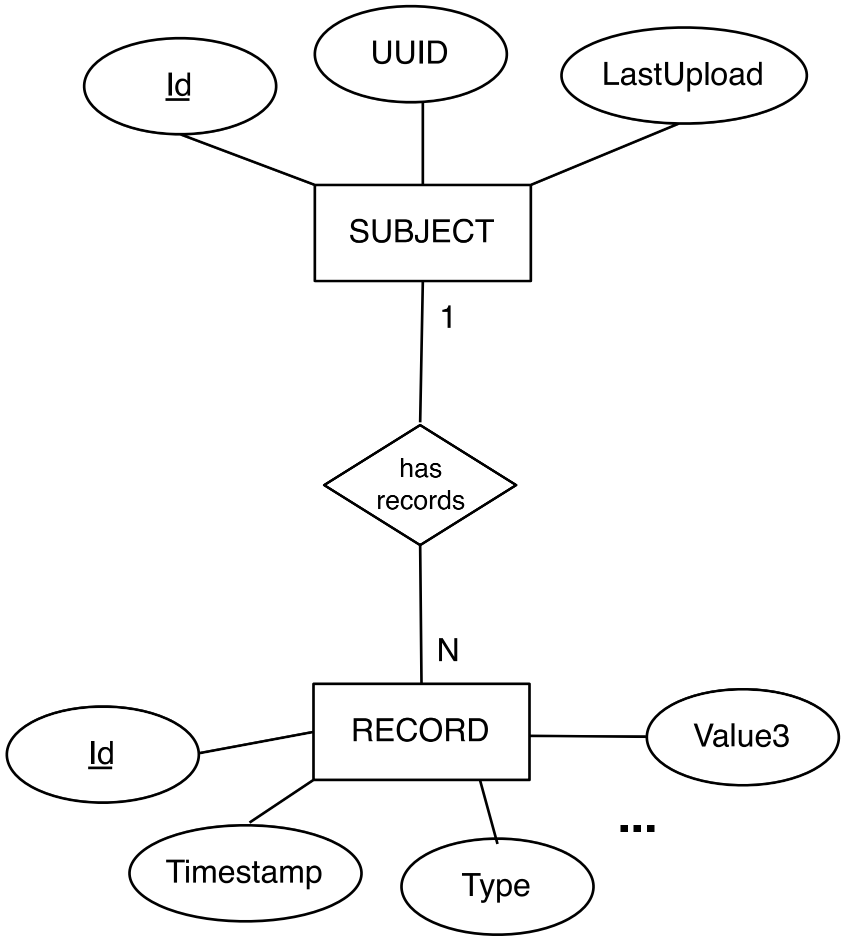

Figure 4.2: EER diagram for cloud database

4.4 Client-Server Communication

As much as possible, we tried to maintain the REST (Representational State Transfer) communication architecture [51]. As mentioned earlier, JSON served as the object notation for uploading records to the server database. The REST verb involved in uploading records to a server is `PUT`. In Figure 4.3, one finds an example of a JSON object for a record that describes a sample from a gyroscope. Observe that an object is simply a set of key/value pairs with keys in double quotation marks on the left of the colon and values on the right of the colon. While strings must appear in double quotation marks, numbers do not.


```
{
    "uuid" : "C055362EA1641F59539271EECDABFE55",
    "type" : 4,
    "value1" : -0.000350952,
    "value2" : 0.00300598,
    "value3" : 0.000198364,
    "timestamp" : 1374603739184,
    "event_timestamp" : 1374603739125565736,
    "upload_timestamp" : 1374603836084,
    "assessment_number" : 1
}
```


Figure 4.3: Example of a JSON object for record from mobile device

Due to the high density of data, it became clear that executing a `PUT` request for each record would take too much time. Consequently, we structured the uploading of records into batches of 1000 at maximum. For each batch, an HTTP `POST` request was made containing the next batch.

4.5 API Structure

Our set of web services for structuring communication between the mobile devices and the cloud server is packaged into an API (Application Programming Interface). There is an upload API and an administrator API. The upload API consists of a single call with which one can pass records from the mobile device to the server. The admin API consists of several calls that allow an administrator to assess the status of the system and access specific records for subjects. Table 4.1 contains a list of the main API calls and basic descriptions of the functionality they provide. Note that all URLs are secured through SSL-based encryption.

API	**URL**	**Description**
Upload	`https://mpeer/api/record` Params: *None*	`POST` records
Admin	`https://mpeer/api/admin/assessments` Params: *id* Returns: JSON	`GET` all assessments for a subject
Admin	`https://mpeer/api/admin` Params: *None* Returns: JSON	Main system dashboard

Table 4.1: API calls and descriptions

4.6 Peer Mentorship System

As has been noted before, the mPeer project of which this thesis forms a part exists in the context of facilitating a mentor-mentee relationship. While we have only developed the data collection app (for the veteran mentee) at this point, we can envision its place alongside another app that will be used by mentors to monitor the progress of the veteran. In a similar project, called iPeer, we have spent much time developing a mentor dashboard that allows mentors to view their veterans and their status, both historically and currently. Since the mPeer project looks to extend the iPeer system, we can imagine that the mentor apps would look similar to each other once they are released.

CHAPTER 5: IMPLEMENTATION

In this chapter, we document the implementation details of the mPeer data collection app developed for the Android platform. We describe the specific development environments and system configurations for both the mobile devices and server. Along the way, we note any significant challenges of implementing this kind of system and how we addressed them.

5.1 Smartphone Configuration

As mentioned before, the mPeer data collection app was developed for the Android platform. The choice of this platform was deliberate and based on the unique nature of the app we developed. In the smartphone operating system world, there are a few major players–Android (Google), iOS (Apple), Windows Phone (Microsoft), and BlackBerry (Research In Motion). According to recent reports, Android and iPhone smartphones accounted for over 90% of the smartphone devices shipped in the first quarter of 2013 [52]. Android smartphones by themselves made up over 50% of all smartphones shipped. In terms of market share, Android and iPhone have a clear dominance over other operating system platforms. The decision to choose Android over the iPhone system for this project came down to the functionality provided by the operating system API. While the iPhone system has a relatively closed API, Android provides a more open one with the specific ability to run applications in the background according to a scheduler. This was the main reason why Android was chosen over iPhone. Android smartphones also provide a greater variety of hardware handsets from a diverse group of manufactures. Because phones will have to be purchased for participants, a lower entry price point is preferable to a higher one.

5.1.1 Development Environment

The development of the mobile app was exclusively performed using the Eclipse IDE (Integrated Development Environment) with Android Development Tools (ADT) build 22.0.0 running on OS X. API (Application Programming Interface) version 17 served as the target SDK (Software Development Kit); although, devices with earlier SDKs were successfully used.

5.1.2 Device Requirements

While efforts have been made to ensure that the application will run successfully (e.g., will not crash) on a variety of devices, there are certain requirements for devices such that they collect all the possible data of interest. At the least, devices must meet the following minimum general characteristics: WiFi, GPS, accelerometer, gyroscope, light sensor, and external storage. Devices with these minimum requirements are available for around $100.

5.1.3 Device Permissions

In order to meet our design goal of unobtrusiveness, the device must be able to perform a variety of operations without user intervention. Consequently, the list of device permissions required became rater extensive. Whereas some permissions such as sensor data are obvious, others such as permission to know when the device has finished booting up are not as apparent at first glance. On the Android platform, permissions requirements are declared in the application manifest file, `AndroidManifest.xml`. Incidentally, the declaration of exhaustive permissions, the inclusion of them in the Google Play store, and the explict consent that users must provide to allow applications those permissions represents a design distinction between the Android ecosystem and the iOS ecosystem.

Permission Constant	Justification
ACCESS_NETWORK_STATE	Determine whether the device is connected to a WiFi network to upload data
ACCESS_FINE_LOCATION	Collect location and speed data from GPS
INTERNET	Use the Internet connection to upload data
READ_CALL_LOG	Read call log to compute call activity metric.
RECEIVE_BOOT_COMPLETED	Determine when the device has booted up successfully so we can start the alarms for data collection
VIBRATE	Activate vibration when self report available
WRITE_EXTERNAL_STORAGE	Store SQLite database on external storage

Table 5.1: Android permission constants and justification

While Android provides programmers with a relatively open development environment (provided that users provide consent for access to system resources), the iOS platform remains relatively closed to developers. It is precisely for this reason that the Android development platform was chosen to build this project. Table 5.1 lists the seven permission constants and a justification for their necessity in the application. Some are functional permissions, in that they allow us to do something. Others are state permissions, in that they allow us to know if something has occurred.

5.2 Server Configuration

Due to its flexibility, ease-of-use, and uptime assurances, a cloud provider was chosen to host the server used in the development. We selected Amazon's Elastic Compute Cloud (EC2) system because of its relative maturity as a cloud provider and low operational cost [53]. The free usage tier offers 750 hours of compute time per month on a micro instance, which has one virtual core and 615 MB of memory. Amazon provides sophisticated monitoring solutions to determine if and when to scale to a larger instance or multiple micro instances. These decisions can occur automatically or by manual intervention.

As there are no regional options for the midwest United States, the micro instance was created in the US West (Oregon) region. A Ubuntu 12.04 (Precise) image was loaded onto the instance and a standard Linux, Apache, MySQL, PHP (LAMP) stack was built on top of it. With the need to access the server's command line, we created a security group with standard open ports for SSH (Secure Shell), HTTP (Hypertext Transport Protocol), and HTTPS (Hypertext Transport Protocol Secure) traffic. Instances are provided both an internal and external IP address through which they are accessible.

5.3 Data Collection

One of the primary goals of this thesis is to provide a working implementation of a sensor data collection system via mobile phones to be used to inform high-risk behavior monitoring. Processing, storing, and uploading high density sensor streams on the smartphone required the development of a framework for doing so. This framework is multithreaded, at the per-sensor level, and is easily extendable to any number or kind of sensor. While there are differences in the implementation of the framework depending on whether a sensor is polled or event driven, the interfaces between the sensor subsystem and its surrounding components are clearly defined and consistent.

5.3.1 Sensor Threads and Services

The mPeer app defines a class called *SenseService*, which is the primary coordinator of sensor data collection. Rather than an Activity, which corresponds to something the user does, a Service corresponds to something the system does (usually without user intervention). Figure 5.1 shows a UML (Unified Modeling Language) diagram for *SenseService* that lists the salient instance variables and methods. We begin with a list of requested sensors, represented by the Android API class *Sensor*. This list can be hardcoded manually or passed to the service via Intent parameters. For each sensor in the list, we create a corresponding *SensorEventProcessor*, which is a custom class that takes a reference to its associated sensor. These *SensorEventProcessor* objects receive sensor events, which are generated whenever a new sensor reading becomes available, and write a record to the phone's SQLite database. Each one of these *SensorEventProcessor*s, which inherit from the Android API class *HandlerThread* runs in its own thread and consequently does not block the main thread of control for the service or MainActivity (if it is running).

SenseService
- selectedSensors : List<Sensor> - sensorEventProcessors : List <Handler>
onHandleIntent(Intent intent) - onSensorChanged(SensorEvent event) - cleanup()

Figure 5.1: UML diagram of SenseService class

Figure 5.2 presents a UML sequence diagram that describes the series of actions that occur within the *SenseService* lifecycle. When the Android system *AlarmManager* creates the *SenseService* on the hour, *SensorEventProcessor*s are created for each sensor specified. The event processors each run in their own thread and simply receive samples from sensors and insert records into the on-phone SQLite database. Once they have run for 60 seconds, the event processors signal that they are done to the *SenseService* object before dying. Once all event processors have returned successfully, the *SenseService* object dies until it is recreated by the *AlarmManager* in one hour's time.

5.3.2 Record Types

The `android.hardware.Sensor` class defines several sensor type constants. Expanding them to include other sensor data such as location, we have used these

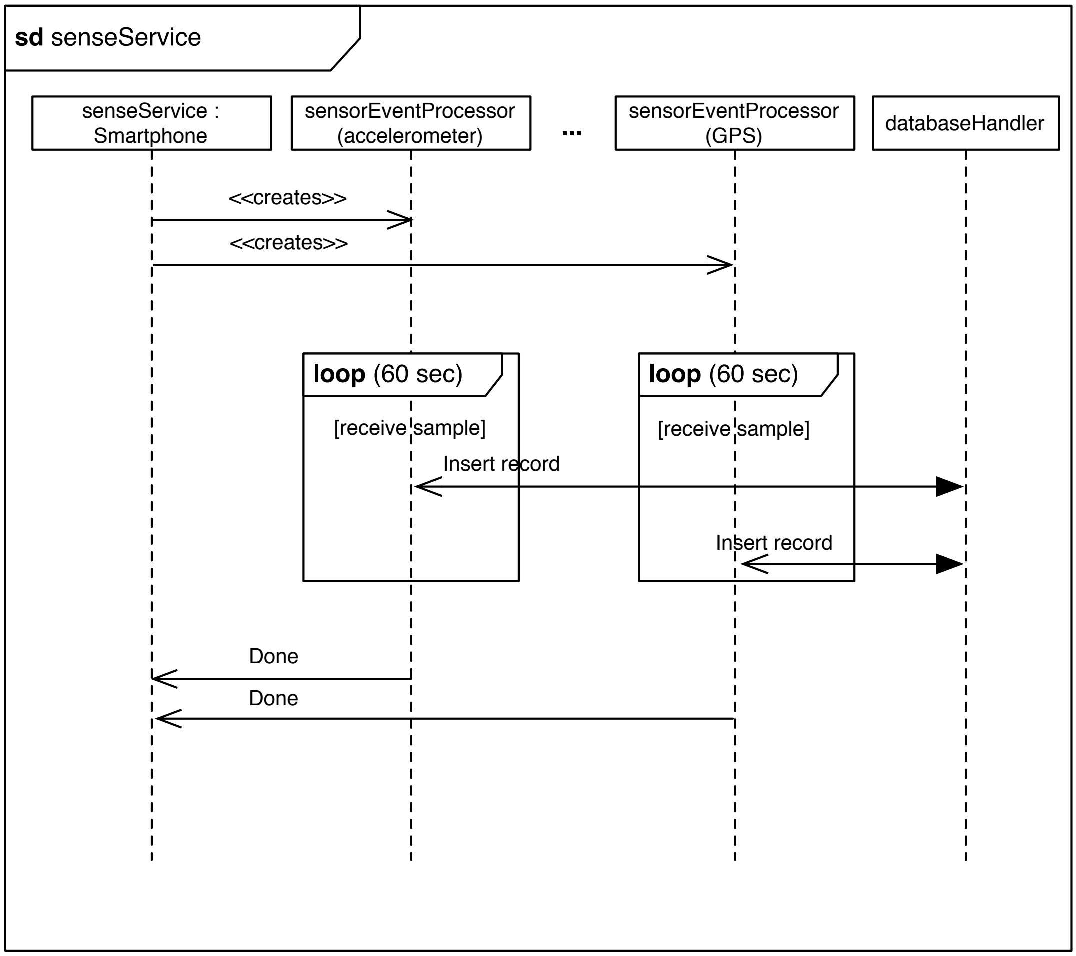

Figure 5.2: UML sequence diagram for SenseService

constants for the "type" attribute of Record. The `android.hardware.SensorEvent` class has an instance variable called "values," which an array of floating point values. Since many of the early sensors have three array values (x, y, and z), the Record table defines three value columns. Table 5.2 shows the variable name used in the Android code. The naming conventions were borrowed from the `Sensor` class when defining our own types (light, battery, GPS, call, and self report). Note that the values chosen for our self-defined types start at 101, whereas the Android values start at 1. The difference highlights which are defined in the `Sensor` class and which are defined by our application. It also separates the value spaces so values from the `Sensor` class and values from the application classes do not overlap.

Variable	Value	Description	Value 1	Value 2	Value 3
`TYPE_ACCELEROMETER`	1	Raw accelerometer	x-axis	y-axis	z-axis
`TYPE_GYROSCOPE`	4	Raw gyroscope	x-axis	y-axis	z-axis
`TYPE_LIGHT`	5	Light	Intensity	-	-
`TYPE_BATTERY`	101	Battery level	Percent	-	-
`TYPE_GPS`	102	GPS coordinates	Latitude	Longitude	Speed
`TYPE_CALL`	103	Telephone metric	Metric	-	-
`TYPE_SELF_REPORT`	104	Self report response	SID	SRID	-

Table 5.2: Sensor type constants for Record table

5.4 Assessment Scheduling

Sensor based assessments are administered by the app every hour. Sensor data collection occurs for a window of 60 seconds in which samples are collected from the accelerometer, gyroscope, GPS, light intensity meter, and battery. The computed telephone metric defined as

$$\begin{gathered}(\text{number of calls dialed} + \text{number of calls received}) - \\ (\text{number of missed or ignored calls} - \text{number of calls returned})\end{gathered}$$

was computed twice daily. The window of 60 seconds was chosen to limit the amount of data collected. Obviously, this leaves open the distinct possibility that the app will miss important events during the remaining 59 minutes of each hour. Because we are interested in understanding the kind of data collected at this point, we were not too concerned about this possibility. Eventually, we will probably want to set specific dynamic timing schedules that respond to certain events.

5.5 Security and Privacy

As with any application that deals with user data, we must ensure that data are secure and that efforts have been made to protect users' privacy. Given that veterans with PSTD have great concerns about privacy and the general reluctance to provide any data that might potentially affect a veteran's ability to receive government benefits, security and privacy become even more important. In this section, we document the specific techniques used to meet these requirements. Development of a security and privacy framework tailored to the needs of veterans and the peer mentorship relationship is being simultaneously addressed by the iPeer project (see chapter 2).

5.5.1 HTTPS

Securing the communication channel between a device and the server is not only good programming practice but also is essential when transferring sensitive data. Since the API uses simple RESTful HTTP calls, this task comes down to implementing an SSL (Secure Socket Layer) connection over HTTP. While a relatively straightforward process, securing an HTTP connection on an Android client remains tricky. We will cover the configuration of SSL on both an Apache web server and an Android client.

On the server side, we assume a standard installation of the Apache2 web server. First we must generate two certificates: the CA (certificate authority) certificate and what we will call the the application certificate. The Android operating system does not allow self-signed certificates; thus, one first generates the CA certificate in order to sign the application certificate.

On the client side, we must provide a Java "keystore" that contains the "certificate chain" (essentially the two certificates created earlier) used to encrypt the connection. Current Java versions include a command-line tool called "keytool" that handles the

Number	Command
1	`openssl genrsa -des3 -out server.key 1024`
2	`openssl rsa -in server.key -out server.key.insecrure`
3	`openssl req -new -key server.key -out server.csr`
4	`open req -x509 -extensions v3_ca -keyout cakey.pem -out \` `cacert.pem -days 3650`
5	`sudo open ssl ca -in server.csr -config /etc/ssl/openssl.cnf`

Table 5.3: SSL commands for generating CA signed SSL certificate

packaging of cryptographic certificates and keys. Android favors the use of the BouncyCastle cryptographic provider service. Once the two certificates are bundled in a Java keystore, the file must be placed in an accessible part of the Android application filesystem. Our application stores the keystore file in the "assets" folder. By default, this folder does not contain any files and can be used to include files that will be preserved in the compiled application and be accessed by name at runtime.

In Figure 5.3 we provide a visual description of this process along with indexes to the required command line instructions for configuration on a Ubuntu LAMP setup as described earlier. The Arabic numbers that appear in the boxes correspond to the command line instructions provided in Table 5.3

5.5.2 UUID Obfuscation

We propose an approach that engages the user in the protection of his own privacy. Our approach asks the user to provide a "passphrase" when running the app for the first time. This passphrase is then concatenated to the UUID string before computing an `md5` hash of the combined string. Figure 5.4 shows a schematic representation of the process of obfuscating the user's UUID. The passphrase is something specific to the user while the UUID is something specific to the device. Combined and then hashed, the resultant string at the bottom of the figure becomes the unique, obfuscated device/user identifier that the app sends to the server when it uploads data.

Note that the obfuscated identifier cannot be easily linked back to the device that sent it. Furthermore, if the user passphrase is compromised the original UUID cannot be easily traced back to the device. Also, since the UUID is unique to the device, if the user uninstalls and then reinstalls the app, he can still recover the obfuscated identifier by using the same passphrase. This process in many ways mimics the common practice of "salting"[1] sensitive information such as passwords or credit card numbers before they are stored in databases. The difference is that the salting occurs on the device rather than on the server. For an explanation of the problems related to using UUIDs to identify users, see chapter 3.

[1] The name invokes the metaphor of throwing salt into a dish before cooking. In the process described here, the "salt" would be the passphrase.

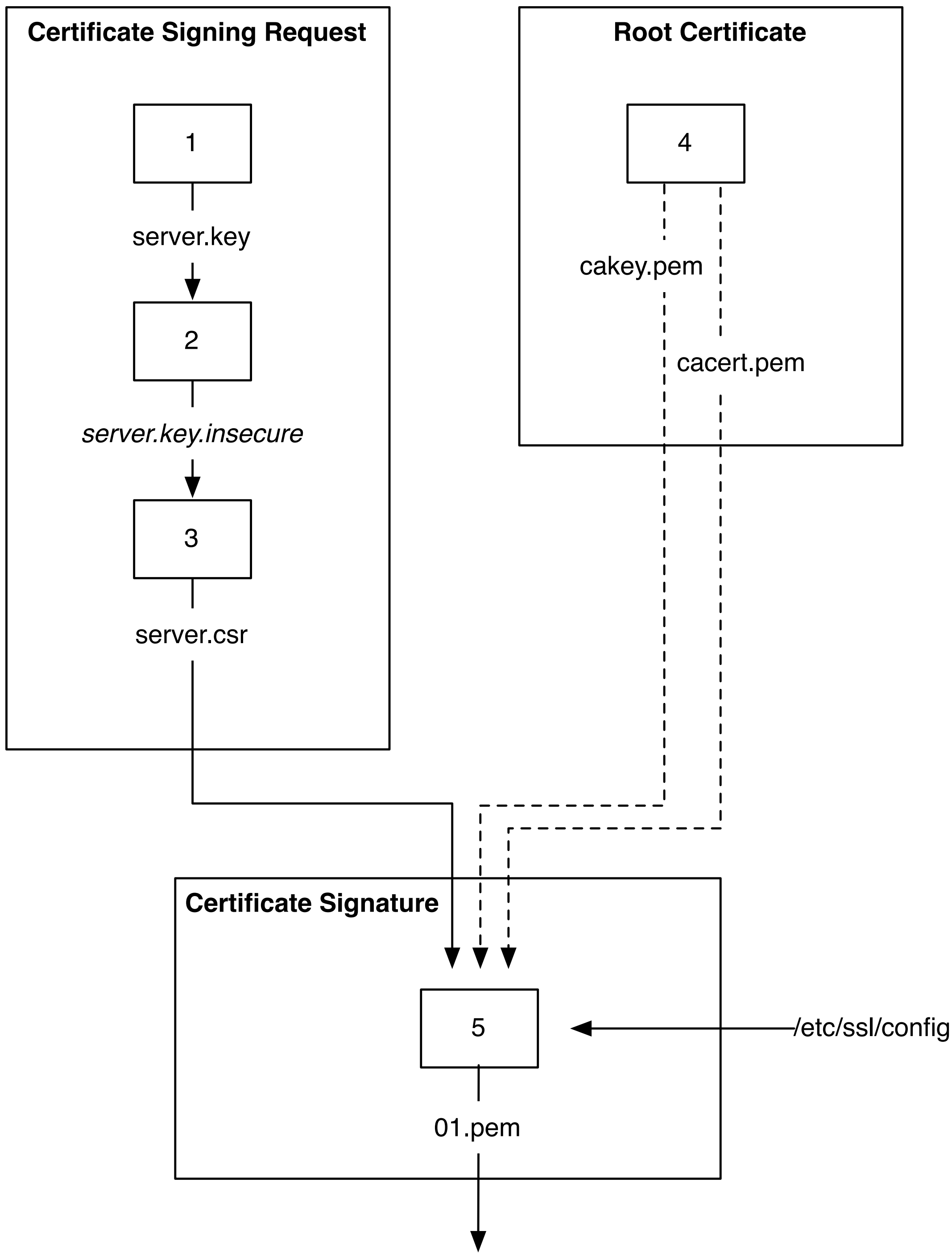

Figure 5.3: Process of generating CA signed SSL certificate

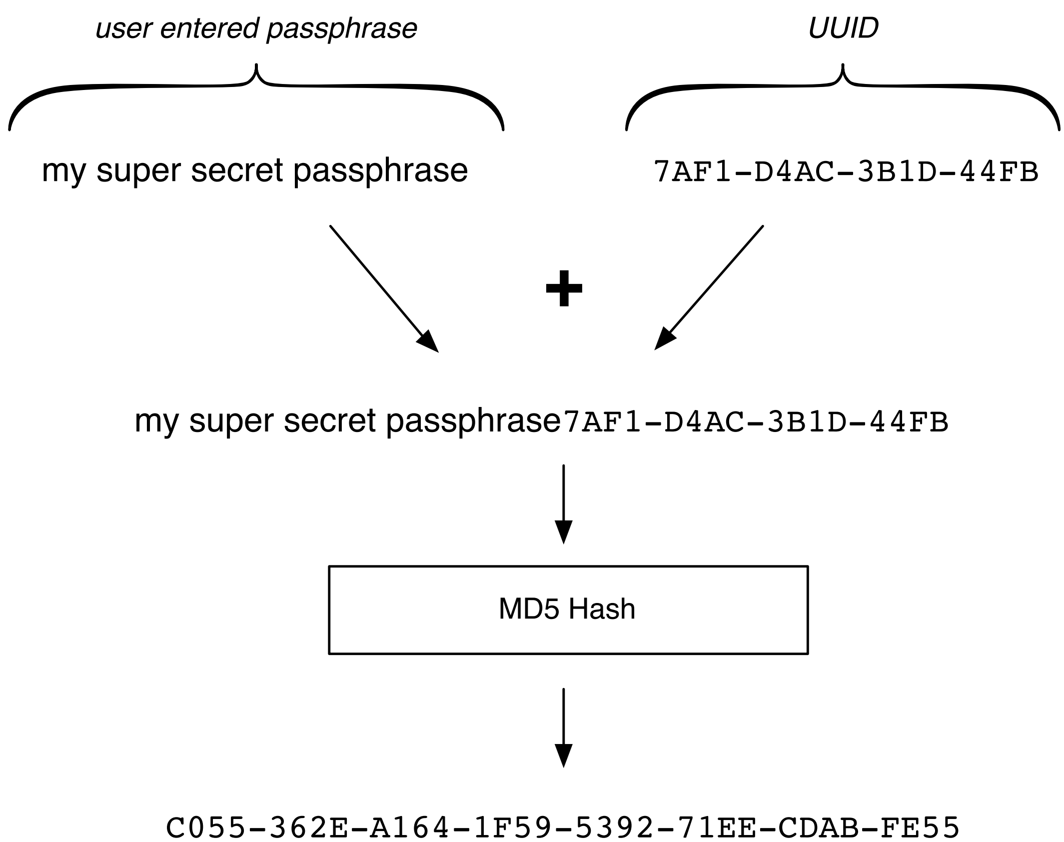

Figure 5.4: Schematic of hashed UUID

CHAPTER 6: DATA COLLECTION AND EVALUATION

After developing a prototype version of the mPeer app, our next step was to collect data on multiple subjects. Our goals for data collection were three fold: first, to collect enough data over time to understand the features that can be extracted; second, to ensure that the system works as intended; third, to identify any weaknesses in the implementation of the system that should be addressed before it is released as part of the CTSI pilot grant. This chapter describes the data collection process from the development of an IRB protocol to observations about the data themselves.

6.1 Marquette IRB Protocol

Marquette University's Institutional Review Board (IRB) approved our data collection protocol on July 9, 2013, under protocol number HR-2645 titled "An mHealth Approach to Monitoring Mental Health." The IRB granted an exemption for the research protocol under "Exemption Category #2: Educational Tests, Surveys, Interviews, or Observations" (United States Code §46.101(b)(2)). As part of the IRB application, a two-page consent form was drafted and subsequently approved. Among other things, this consent form outlines a seven-step procedure for individuals to follow as part of their participation in the research protocol.

As part of the protocol, five participants were recruited from the Ubicomp Lab at the Department of Mathematics, Statistics, and Computer Science at Marquette University. Because our goals stated above are more concerned with testing the system and gathering preliminary data using the system, we did not feel it necessary to recruit actual veterans to serve as participants. While more than five graduate students responded to the opportunity to participate, only five ultimately became part of the study. The requirement that students own an Android phone as their primary mobile device limited the number of participants.

The informed consent document prepared as part of the protocol enumerates a seven-step procedure to be followed during the data collection period. The steps were:

1. You will download the smartphone application from the Ubicomp Lab's secure server and install it on your smartphone device.
2. You will receive approximately 15 minutes of training about the smartphone application.
3. Data collection will be started and an initial communication of data will be attempted.
4. The research project will last for two weeks. The following data will be downloaded from your phone daily: accelerometer data, gyroscope data, GPS data, ambient light measurements, and survey response data.
5. A pop-up will occur on the phone daily with a brief survey for you to complete.
6. In two weeks' time, you will meet with the principal investigator to collect any remaining data left on the phone.
7. You will be asked to delete the application from your smartphone.

For specific durations mentioned, like the two weeks of data collection and the 15 minutes of training, were selected to guarantee an upper bound on the necessary time required for those steps. While no subjects ran the application for a full two weeks, subjects ran it for varying lengths of time. The data that have been chosen for further analysis represent a window of one week during which all subjects were running the app. Due to issues with scheduling and availability, it was not possible to meet with all subjects simultaneously. Furthermore, there were a handful of instances where subjects expressed an issue with the application that required building a slightly new version.

6.2 Data Collection Structure

Data collection from students began on Tuesday, July 23, 2013, and concluded on Friday, August 3, 2013. To obtain a week of overlapping data from all participants, data were trimmed to run from Friday, July 26, 2013, to Friday August 3, 2013. Under full compliance to the daily self-report survey and continuous battery life, this would mean that we would have 7 surveys and around 170 sensor data assessments per participant.

Figure 6.1 shows the total number of records collected over the week for each subject. The varying number of records can be traced back to the default sampling frequency of different devices. The Android SDK only allows a programmer to specify which of four delay values to use for each sensor (user interface, normal, game, and fastest). For the app, the game delay was used for the accelerometer and gyroscope. The effective sample rate obtained by devices is hardware dependent: this is why the SDK specifies functional delay options rather than specific sampling rates. Because nearly all devices used were different, the same delay option yielded markedly different effective sample rates.

6.3 Self Reported Data

Our eventual goal is to be able to use sensor data and other contextual information to infer the responses to questions on interest. In order to investigate this possibility, we must select which questions are of interest. To validate the system operation, we selected five questions from a standard instrument called the Social Functioning Questionnaire [54]. The selection of a limited set of questions was chosen not only to limit the size of the data collected but also to lessen the burden to the student

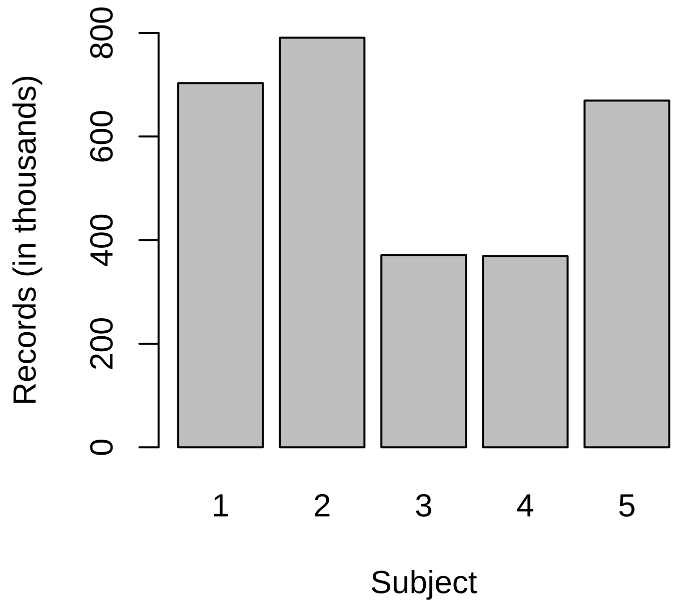

Figure 6.1: Number of records for each subject

testers. Table 6.1 enumerates the questions selected that formed the self report.

Number	**Statement**
1	I complete my tasks at work and home satisfactorily.
2	I find my tasks at work and at home very stressful.
3	I have no money problems.
4	I get on well with my family and other relatives.
5	I enjoy my spare time.

Table 6.1: Statements from Social Functioning Questionnaire

Respondents are prompted to select the extent to which they agree with the statement provided. The option choices are: very much, sometimes, not often, or not at all. These responses have integer scores associated with them, as seen in Table 6.2.

Example responses for subject 4 are provided in Figure 6.2. The days of the week run along the x-axis and response scores run along the y-axis. A close observer will notice that subject 4 did not have a response on Sunday. This indicates that the subject probably did not respond to the daily notification to fill out the self report. There was no mechanism implemented to remind or follow up with people if they did not respond to the

Score	Response
1	Very much
2	Sometimes
3	Not often
4	Not at all

Table 6.2: Response scores for Social Functioning Questionnaire

notification. One of the future works of this project, and others of this kind, will be to examine questions around motivating users to respond to system prompts.

6.4 Sensor Data

Sensor data were collected from participants each hour during the week-long window. Figure 6.3 shows accelerometer and gyroscope sensor data for each of their three respective axes for subject 4 around the time that he filled out the self-report on the second day of data collection.

6.5 Weaknesses

During the data collection period, we observed several weaknesses in the system that should be addressed before the app is released as part of the grant. We identify two of the main ones in this section related to data communication and Internet connectivity.

6.5.1 Data Communication

While JSON formatted object notation is less verbose than its XML competitor, it still takes an unacceptably long time to generate, send, and parse when dealing with large amounts of high-frequency data. This time can be attributed to a few observations. First, the standard Java library for generating JSON, `org.json.*`, takes a substantial amount of time to assemble a file for upload. Second, the transfer time over HTTPS is longer than that over HTTP. Third, the parsing of the JSON file and subsequent entry into the database takes time as well. Despite a tendency to favor more object-oriented data

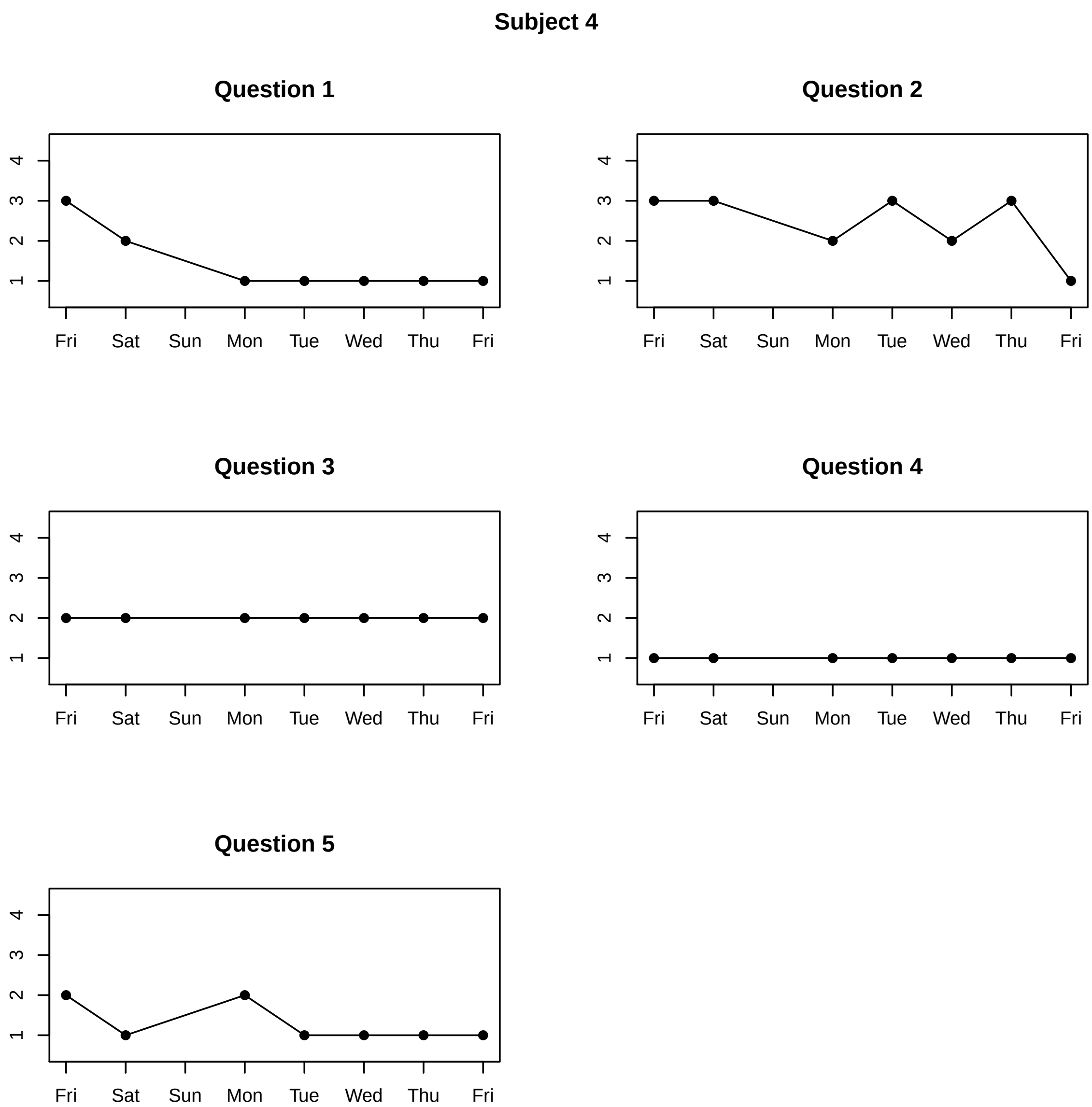

Figure 6.2: Self report responses for subject 4

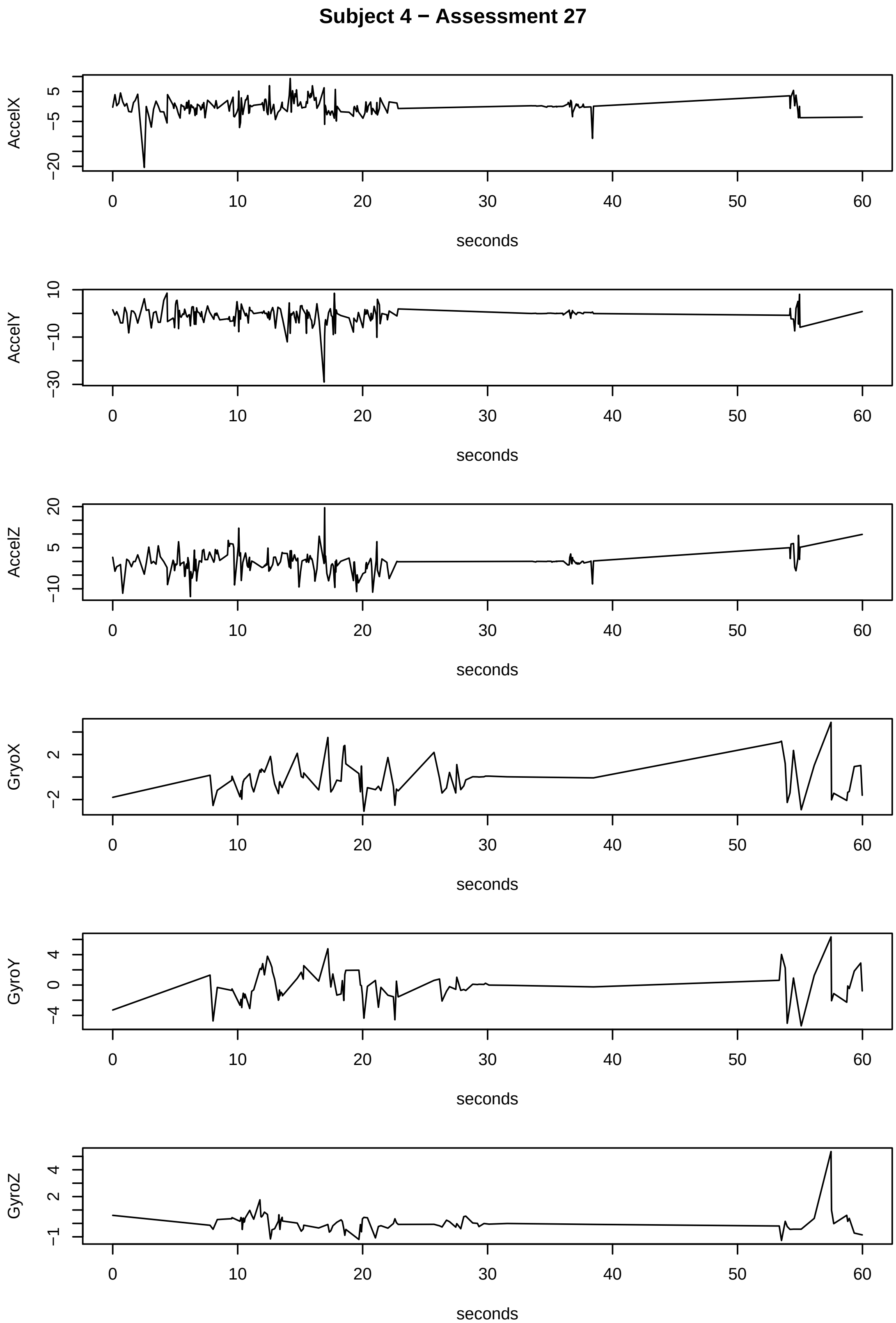

Figure 6.3: Sensor data for subject 4 from second day

transfer representations like REST or SOAP, it would probably be more appropriate to use a more lightweight protocol. Considering that the data transfer is essentially database-to-database, a direct database connection might be an approach. Alternatively, some kind of streaming, non-text based approach could be contemplated add well. Maintaining the goal of a near real-time system would benefit from faster data uploads.

6.5.2 Internet Connectivity

The app only initiates uploads from the device when a WiFi connection is available. Given that high-density data are being generated every hour, lack of a WiFi connection can create a backlog of records on the device. One approach to consider is to prioritize the data based on relevance to the system. For example, in the case where there is long backlog of records, more recent records could be uploaded first before older ones. There are certain kinds of data that we should be able to be uploaded over the cellular connection. One can imagine emergent data and basic device status updates should be granted this privilege.

CHAPTER 7: Conclusion

Providing new and innovative care for returning veterans with mental health issues continues to be a major national priority. A recent executive order from President Obama [55] and several calls for proposals underscore this priority. As mobile health has emerged as a potential game changer in the delivery of healthcare, the extension of mobile health principles and strategies becomes a natural approach to providing care to returning veterans. Attending to the needs of recent veterans requires providing greater support outside of the traditional VA hospitals. Outreach from the VA to communities has begun but more must be done. Community partners, like Dryhootch of America, our community sponsor for this project, have great access to and trust within the veteran community. Developing a mobile health approach to monitoring veteran mental health, specifically PTSD, is a transdisciplinary endeavor that involves multiple stakeholders from varying backgrounds and experiences.

In this thesis, we presented mPeer, a smartphone-based monitoring system for veterans with PTSD that begins the work of bringing smartphone technology to bear on the issues that returning veterans face. One of the immediate next steps is to begin more structured analysis of the data collected from the student volunteers and develop the *a priori* algorithm for high-risk behavior detection. Bridging the gap from self-reported data to sensor data will require delving into machine learning algorithms. The first step here would be to frame the analysis in some kind of manageable way. For example, one can imagine that linking self-reported data to sensor data could be thought of as a time-series based classification problem. This problem of connecting the self-reports with the sensor data also will be crucial in the process of demonstrating that sensor data alone are effective in detecting high-risk behavior.

Another next step is to begin to understand specific exemplar cases of high-risk behavior. Building knowledge around how a few specific behaviors can be detected and tracked through smartphone sensors will be key to decomposing the larger task of behavior detection into manageable pieces. Given the kind of population that the app targets, we most likely will have strong signals that can indicate that something is wrong. We are not interested in the small minutiae of behavior but rather more general patterns of behavior.

Recalling that the system described in this thesis will exist within the context of a peer mentoring relationship, we must consider how the analysis provided by the system fits into the workflow of peer mentors. In many ways, the peer mentors are attempting to obtain a "360 degree" assessment of their veteran mentees. How we incorporate assessments, of a variety of kinds and sources, into meaningful information to peer mentors remains important. We need to be mindful of the peer mentors and their work flow while developing these tools.

As the project continues forward, a variety of practical considerations arise as we move from system design to deployment. Implementing more robust privacy models will be important to ensure trust in the system. Selecting which questions to ask in the self report and how often to ask those questions still has to be completed. The specifics of how data are to be uploaded from veterans' devices to the server have to be discussed and finalized.

Some have also suggested that a system like ours has potential applications in other areas. One can imagine its applicability to any kind of behavioral observation or therapy situation.

BIBLIOGRAPHY

[1] L. J. Bilmes, "Current and projected future costs of caring for veterans of the Iraq and Afghanistan wars," Jun. 2011. [Online]. Available: http://costsofwar.org/article/caring-us-veterans

[2] C. S. Milliken, J. L. Auchterlonie, and C. W. Hoge, "Longitudinal assessment of mental health problems among active and reserve component soldiers returning from the Iraq war," *JAMA: the journal of the American Medical Association*, vol. 298, no. 18, pp. 2141–2148, Nov. 2007.

[3] D. West, "How mobile devices are transforming healthcare," May 2012. [Online]. Available: http://www.brookings.edu/research/papers/2012/05/22-mobile-health-west

[4] B. Obama, "Remarks by the President at 93rd annual conference of the American Legion," Aug. 2011. [Online]. Available: http://www.whitehouse.gov/the-press-office/2011/08/30/remarks-president-93rd-annual-conference-american-legion

[5] Institute of Medicine, *Returning Home from Iraq and Afghanistan Assessment of Readjustment Needs of Veterans, Service Members, and Their Families.* Washington, DC: National Academies Press, 2010.

[6] M. S. Kaplan, B. H. McFarland, N. Huguet, and M. Valenstein, "Suicide risk and precipitating circumstances among young, middle-aged, and older male veterans," *American Journal of Public Health*, vol. 102 Suppl 1, pp. S131–137, Mar. 2012.

[7] T. L. Tanielian and Rand Corporation, *Invisible wounds of war: psychological and cognitive injuries, their consequences, and services to assist recovery.* Santa Monica, CA: RAND, 2008.

[8] H. Seal, D. Bertenthal, C. Miner, S. Sen, and C. Marmar, "Bringing the war back home: Mental health disorders among 103 788 us veterans returning from iraq and afghanistan seen at department of veterans affairs facilities," *Archives of Internal Medicine*, vol. 167, no. 5, pp. 476–482, Mar. 2007.

[9] R. Kessler, P. Berglund, O. Demler, R. Jin, K. Merikangas, and E. Walters, "Lifetime prevalence and age-of-onset distributions of dsm-iv disorders in the national comorbidity survey replication," *Archives of General Psychiatry*, vol. 62, no. 6, pp. 593–602, Jun. 2005.

[10] R. Kessler, W. Chiu, O. Demler, and E. Walters, "Prevalence, severity, and comorbidity of 12-month DSM-IV disorders in the national comorbidity survey replication," *Archives of General Psychiatry*, vol. 62, no. 6, pp. 617–627, Jun. 2005. [Online]. Available: http://dx.doi.org/10.1001/archpsyc.62.6.617

[11] R. D. Marshall, M. Olfson, F. Hellman, C. Blanco, M. Guardino, and E. L. Struening, "Comorbidity, impairment, and suicidality in subthreshold PTSD," *The American Journal of Psychiatry*, vol. 158, no. 9, pp. 1467–1473, Sep. 2001.

[12] American Psychological Association, *Diagnostic and statistical manual of mental disorders : DSM-5.* Arlington, VA : American Psychiatric Association, c2013., 2013.

[13] S. Laxminarayan and R. S. H. Istepanian, "UNWIRED e-MED: the next generation of wireless and internet telemedicine systems," *IEEE Transactions on Information Technology in Biomedicine*, vol. 4, no. 3, pp. 189–193, 2000.

[14] R. S. H. Istepanian and J. Lacal, "Emerging mobile communication technologies for health: some imperative notes on m-health," in *Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2003*, vol. 2, 2003, pp. 1414–1416 Vol.2.

[15] R. Istepanian, E. Jovanov, and Y. Zhang, "Guest editorial introduction to the special section on m-health: Beyond seamless mobility and global wireless health-care connectivity," *IEEE Transactions on Information Technology in Biomedicine*, vol. 8, no. 4, pp. 405–414, 2004.

[16] R. S. H. Istepanian, S. Laxminarayan, and C. S. Pattichis, *M-health emerging mobile health systems*. New York, NY: Springer, 2005.

[17] mHealth Alliance, "Frequently asked questions," 2009. [Online]. Available: mHealthAlliance

[18] Dryhootch, "About dryhootch." [Online]. Available: http://dryhootch.org/page/about-dryhootch-1

[19] National Center for Telehealth and Technology, "About t2," 2013. [Online]. Available: http://t2health.org/about.html

[20] US Department of Veterans Affairs, "PTSD coach," Jun. 2013. [Online]. Available: http://www.t2health.org/apps/ptsd-coach

[21] E. B. Blanchard, J. Jones-Alexander, T. C. Buckley, and C. A. Forneris, "Psychometric properties of the PTSD checklist (PCL)," *Behaviour Research and Therapy*, vol. 34, no. 8, pp. 669–673, Aug. 1996.

[22] US Department of Veterans Affairs, "PE coach," Jul. 2013. [Online]. Available: http://t2health.org/apps/pe-coach

[23] E. B. Foa, E. A. Hembree, and B. O. Rothbaum, *Prolonged exposure therapy for PTSD: emotional processing of traumatic experiences : therapist guide*. Oxford; New York: Oxford University Press, 2007.

[24] S. Woodward, "Enhancing emotion regulation during driving in OEF/OIF veterans," Apr. 2011. [Online]. Available: http://clinicaltrials.gov/show/NCT01336764

[25] J. Dao, "Help available for drivers who have wartime trauma," *The New York Times*, Jan. 2012. [Online]. Available: http://www.nytimes.com/2012/01/11/us/post-traumatic-stress-disorder-may-cause-erratic-driving.html

[26] B. O. Rothbaum, L. F. Hodges, R. D. Alarcón, D. J. Ready, F. Shahar, K. Graap, J. Pair, P. Hebert, D. Gotz, B. Wills, and D. Baltzell, "Virtual reality exposure therapy for PTSD vietnam veterans: a case study," *Journal of Traumatic Stress*, vol. 12, no. 2, pp. 263–271, 1999.

[27] B. O. Rothbaum, A. S. Rizzo, and J. Difede, “Virtual reality exposure therapy for combat-related posttraumatic stress disorder,” *Annals of the New York Academy of Sciences*, vol. 1208, no. 1, pp. 126–132, 2010.

[28] E. B. Foa, “Prolonged exposure therapy: past, present, and future,” *Depression and Anxiety*, vol. 28, no. 12, pp. 1043–1047, 2011.

[29] E. B. Foa, B. O. Rothbaum, D. S. Riggs, and T. B. Murdock, “Treatment of posttraumatic stress disorder in rape victims: A comparison between cognitive-behavioral procedures and counseling,” *Journal of Consulting and Clinical Psychology*, vol. 59, no. 5, pp. 715–723, 1991.

[30] A. Eftekhari, J. Ruzek, Crowley JJ, C. Rosen, M. Greenbaum, and B. Karlin, “Effectiveness of national implementation of prolonged exposure therapy in veterans affairs care,” *JAMA Psychiatry*, pp. –, Jul. 2013.

[31] S. Kumar, W. J. Nilsen, A. Abernethy, A. Atienza, K. Patrick, M. Pavel, W. T. Riley, A. Shar, B. Spring, D. Spruijt-Metz, D. Hedeker, V. Honavar, R. Kravitz, R. Craig Lefebvre, D. C. Mohr, S. A. Murphy, C. Quinn, V. Shusterman, and D. Swendeman, “Mobile health technology evaluation: The mHealth evidence workshop,” *American Journal of Preventive Medicine*, vol. 45, no. 2, pp. 228–236, Aug. 2013.

[32] A. A. Stone and S. Shiffman, “Ecological momentary assessment (EMA) in behavorial medicine,” *Annals of Behavioral Medicine*, vol. 16, no. 3, pp. 199–202, 1994.

[33] S. Shiffman, A. A. Stone, and M. R. Hufford, “Ecological momentary assessment,” *Annual Review of Clinical Psychology*, vol. 4, no. 1, pp. 1–32, 2008.

[34] D. S. Courvoisier, M. Eid, T. Lischetzke, and W. H. Schreiber, “Psychometric properties of a computerized mobile phone method for assessing mood in daily life,” *Emotion*, vol. 10, no. 1, pp. 115–124, 2010.

[35] D. S. Courvoisier, M. Eid, and T. Lischetzke, “Compliance to a cell phone-based ecological momentary assessment study: the effect of time and personality characteristics,” *Psychological assessment*, vol. 24, no. 3, pp. 713–720, Sep. 2012.

[36] M. Tuomenoksa, “ilumivu: Ecological momentary assessment,” 2013. [Online]. Available: http://www.ilumivu.com/index.php?section=41&chapter=54

[37] D. Daugherty, “iHabit,” 2011. [Online]. Available: http://ihabit4life.com/

[38] Paco, “Paco - the personal analytics companion,” 2013. [Online]. Available: http://paco.googlecode.com/git-history/e84e8aa37449321fc88864723391ed03a314547f/Paco-Server/war/observer.html

[39] T. Conner, “Experience sampling and ecological momentary assessment with mobile phones,” May 2013. [Online]. Available: http://www.otago.ac.nz/psychology/otago047475.pdf

[40] M. Hammarberg and S. M. Silver, “Outcome of treatment for post-traumatic stress disorder in a primary care unit serving vietnam veterans,” *Journal of traumatic stress*, vol. 7, no. 2, pp. 195–216, Apr. 1994.

[41] D. R. Johnson, R. Rosenheck, A. Fontana, H. Lubin, D. Charney, and S. Southwick, "Outcome of intensive inpatient treatment for combat-related posttraumatic stress disorder," *The American Journal of Psychiatry*, vol. 153, no. 6, pp. 771–777, Jun. 1996.

[42] T. L. Hartl, C. Rosen, K. Drescher, T. T. Lee, and F. Gusman, "Predicting high-risk behaviors in veterans with posttraumatic stress disorder," *The Journal of Nervous and Mental Disease*, vol. 193, no. 7, pp. 464–472, Jul. 2005.

[43] A. M. Kelley, J. R. Athy, T. H. Cho, B. Erickson, M. King, and P. Cruz, "Risk propensity and health risk behaviors in U.S. army soldiers with and without psychological disturbances across the deployment cycle," *Journal of Psychiatric Research*, vol. 46, no. 5, pp. 582–589, May 2012.

[44] R. Widome, S. M. Kehle, K. F. Carlson, M. N. Laska, A. Gulden, and K. Lust, "Post traumatic stress disorder (PTSD) and health risk behaviors among Afghanistan & Iraq war veterans attending college," *American Journal of Health Behavior*, vol. 35, no. 4, pp. 387–392, Jul. 2011.

[45] InvenSense, "MPU-600/6050 six-axis (gyro + accelerometer) MEMS motion tracking devices," 2013. [Online]. Available: http://www.invensense.com/mems/gyro/mpu6050.html

[46] M. Sun and J. Hill, "A method for measuring mechanical work and work efficiency during human activities," *Journal of Biomechanics*, vol. 26, no. 3, pp. 229–241, Mar. 1993. [Online]. Available: http://www.sciencedirect.com/science/article/pii/002192909390361H

[47] H. Junker, P. Lukowicz, and G. Troster, "Sampling frequency, signal resolution and the accuracy of wearable context recognition systems," in *Eighth International Symposium on Wearable Computers, 2004. ISWC 2004*, vol. 1, 2004, pp. 176–177.

[48] N. Perlroth, "BITS; hackers post ID numbers for Apple devices, claiming they are from F.B.I." *The New York Times*, Sep. 2012. [Online]. Available: http://query.nytimes.com/gst/fullpage.html

[49] K.-M. Cutler, "Amid privacy concerns, apple has started rejecting apps that access UDIDs," Mar. 2012. [Online]. Available: http://techcrunch.com/2012/03/24/apple-udids/

[50] L. J. Damschroder, J. L. Pritts, M. A. Neblo, R. J. Kalarickal, J. W. Creswell, and R. A. Hayward, "Patients, privacy and trust: patients' willingness to allow researchers to access their medical records," *Social Science & Medicine (1982)*, vol. 64, no. 1, pp. 223–235, Jan. 2007.

[51] R. Fielding, "Architectural styles and the design of network-based software architectures," Dissertation, University of California—Irvine, Irvine, CA, 2000.

[52] IDC, "Android and iOS combine for 92.3% of all smartphone operating system shipments in the first quarter while windows phone leapfrogs BlackBerry," Framingham, MA, Press Release, May 2013. [Online]. Available: http://www.idc.com/getdoc.jsp?containerId=prUS24108913

[53] Amazon, "Amazon elastic compute cloud (Amazon EC2), cloud computing servers," http://aws.amazon.com/ec2/, 2013. [Online]. Available: http://aws.amazon.com/ec2/

[54] P. Tyrer, U. Nur, M. Crawford, S. Karlsen, C. MacLean, B. Rao, and T. Johnson, "The social functioning questionnaire: A rapid and robust measure of perceived functioning," *International Journal of Social Psychiatry*, vol. 51, no. 3, pp. 265–275, Sep. 2005.

[55] B. Obama, "Executive order 13625 of August 31, 2012: Improving access to mental health services for veterans, service members, and military families," Aug. 2012. [Online]. Available: http://www.gpo.gov/fdsys/pkg/FR-2012-09-05/pdf/2012-22062.pdf