Motivational and Intervention Systems and Monitoring with mHealth Tools

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MOTIVATIONAL AND INTERVENTION SYSTEMS AND MONITORING WITH MHEALTH TOOLS

by

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ABSTRACT

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Use of mobile and telecommunication technologies has become widespread in the last decade. With this development, use of mobile devices in healthcare (mHealth) is also increasing. Mobile phones, smartphones, and other mobile devices are affordable tools for different health-related services. In my research, with my research team I have helped to develop several mHealth tools to address the quality of life of cancer survivors, cancer patients and individuals at increased risk for cancer. Tobacco smoking is the major cause of several types of often-fatal cancers and cardio-respiratory diseases. Optimally, we hypothesize that the most effective mHealth tools should be customized and personalized. For smokers, the goal is to encourage cessation. For cancer survivors, one goal is to increase physical activity, which is associated with decreased rates of recurrent disease. In patients with incurable cancers, efficient and current monitoring of symptoms should contribute to better palliation. This dissertation explores multiple issues in use of mHealth tools with these medical populations. We discuss a general framework for collecting and managing healthcare data and mathematical models for data analysis. The specific contributions of this dissertation are: 1.) The design and development of a culturally tailored customized text messaging system for motivation and intervention; 2.) The design and development of a data collection system for an mHealth intervention, and; 3.) A model for monitoring pain levels using mobile devices.

ACKNOWLEDGMENTS

Golam Mushih Tanimul Ahsan, B.S., M.S.

In no particular order, I would like to thank my mother, my father, my brother, my wife, and my friends. I would like to thank my teachers, my faculty, my committee, and my director. I would like to thank the Graduate School and all of the Marquette University administration.

DEDICATION

I would like to dedicate this work to my ever-supporting family and friends.

Thank You

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CHAPTER 1

INTRODUCTION

Mobile phones are prevalent in the world at this moment. According to Statistica, there are about 4.77 billion mobile phone users in the year 2017 [79]. Among them, nearly 2.32 billion people are smartphone users [80]. Modern smartphones come with a variety of sensors. The camera is an essential part of most phones, and one of the most used sensors. There are several other sensors, such as the gyroscope, GPS, accelerometer, etc. Having the ability to connect with many people and the ability to have all these sensors opens a door for mobile phones to be used in healthcare. Healthcare professionals now use not only the phones but also tablets and other mobile devices to collect data from individuals and provide healthcare services.

This dissertation focuses on developing an mHealth System that utilizes the prevalence of mobile devices and combines several mHealth tools into the system. This dissertation also tries to improve mathematical models for diagnosis of pain level using image captures. The basic components of the dissertation are: 1.) A customized and culturally tailored text messaging system for smoking cessation and physical activity for cancer survivors; 2.) A survey system for capturing medical data from participants in a motivational program, and; 3.) An approach to detecting pain levels from symptoms and images.

1.1 Motivation

Scenario 1: A person who plans to quit smoking may become less motivated after a few days and can start smoking again. A personalized and customized text messaging system, which collects information from the participant, can be very helpful to keep the person motivated. An individual from a specific cultural background may be helped by a system that uses culturally tailored text messages.

Scenario 2: Regular physical activity is essential for a cancer survivor. Such participants require regular motivation and keep a journal to stay motivated to have the necessary regular physical activities. It is critical to have a motivational system with text messages and a survey system to collect information about the status of the participants and to help motivate them.

Scenario 3: A person who has cancer needs palliative care. An important sign of that person's well being is the level of pain the person is suffering. It would be helpful if the caregiver could detect the pain level automatically from the facial images of the person and thus prioritize their care.

From these scenarios, we find several major challenges that can be helped through using mHealth tools. We will discuss the challenges and our solutions in the following chapters. Our solutions include:

1. A text messaging system that sends culturally tailored and customized motivational messages.
2. A survey system to acquire data from participants about their state in an intervention or a motivational program.
3. Develop a mathematical model for detecting pain level using a smartphone and other symptom parameters.

1.2 Dissertation Focus

It is possible to develop a system with different mHealth tools for non-invasive monitoring and intervention of different types of patients. It is also possible to have a mathematical model to analyze health data to diagnose the condition of a patient.

1.3 Dissertation organization

We discuss the research challenges in the following chapters. In Chapter 2, we will discuss the basic architecture and data flow of our solution system. In Chapter 3, we will discuss the text messaging intervention system used in Smoking Cessation. In Chapter 4 we will discuss the motivational system used for Physical Activity for Cancer Survivors(PACS). In Chapter 5, we discuss the comparison between these systems. In Chapter 6, we will discuss the total data collection survey system used in Smoking Cessation. Next, in Chapter 7 we describe how we plan to detect pain levels from the facial images from a smartphone camera and symptom values. In all these chapters, we discuss the motivation, related works, details of our solution approach and our analyzed results.

1.4 Publications

Followings are some publications from the work described in this dissertation.

- **Golam Mushih Tanimul Ahsan**, Ivor D Addo, S Iqbal Ahamed, Daniel Petereit, Shalini Kanekar, Linda Burhansstipanov, and Linda U Krebs. ”Toward an mHealth intervention for smoking cessation”. In: Computer Software and Applications Conference Workshops (COMPSACW), 2013 IEEE 37th Annual. IEEE. 2013, pp. 345350.
- **Golam Mushih Tanimul Ahsan**, Drew Williams, Ivor D Addo, S Iqbal Ahamed, Daniel Petereit, Linda Burhansstipanov, Linda U Krebs, and Mark Dignan. ”A Mobile Survey Tool for Smoking Dependency Among Native

Americans”. In: International Conference on Smart Homes and Health Telematics. Springer International Publishing. 2014, pp. 213218.

- Md Kamrul Hasan, **Golam Mushih Tanimul Ahsan**, Sheikh Iqbal Ahamed, Richard Love, and Reza Salim. ”Pain Level Detection From Facial Image Captured by Smartphone”. In: Journal of Information Processing 24.4 (2016), pp. 598608.
- Mohammad Adibuzzaman, Colin Ostberg, Sheikh Ahamed, Richard Povinelli, Bhagwant Sindhu, Richard Love, Ferdaus Kawsar, and **Golam Mushih Tanimul Ahsan**. ”Assessment of pain using facial pictures taken with a smartphone”. In: Computer Software and Applications Conference (COMPSAC), 2015 IEEE 39th Annual. Vol. 2. IEEE. 2015, pp. 726731.
- Richard Reed Love, Tahmina Ferdousy, Bishnu D Paudel, Shamsun Nahar, Rumana Dowla, Mohammad Adibuzzaman, **Golam Mushih Tanimul Ahsan**, Miftah Uddin, Reza Salim, and Sheikh Iqbal Ahamed. ”Symptom Levels in Care-Seeking Bangladeshi and Nepalese Adults With Advanced Cancer”. In: Journal of Global Oncology (2016), JGO004119.
- Linda Burhansstipanov, Linda U. Krebs, Daniel Petereit, Mark B. Dignan, Sheikh Iqbal Ahamed, Michele Sargent, Kristin Cina, Kimberly Crawford, Doris Thibeault, Simone Bordeaux, Shalini Kanekar, **Golam Mushih Tanimul Ahsan**, Drew Williams, and Ivor Addo. ”Reality Versus Grant Application Research ’Plans’”. In: Health Promotion Practice (2017).

CHAPTER 2

SYSTEM DESIGN AND ARCHITECTURE

2.1 General System

Here we will describe the general structure of our system. In most of our systems, the general structure and flow are similar. We customize this structure according to our necessity.

2.1.1 Architecture

We have several layers in our system. At the very bottom of the system, we have the database. To ensure anonymity, data is stored without any personally identifiable items. On top of the database, we have several types of web services

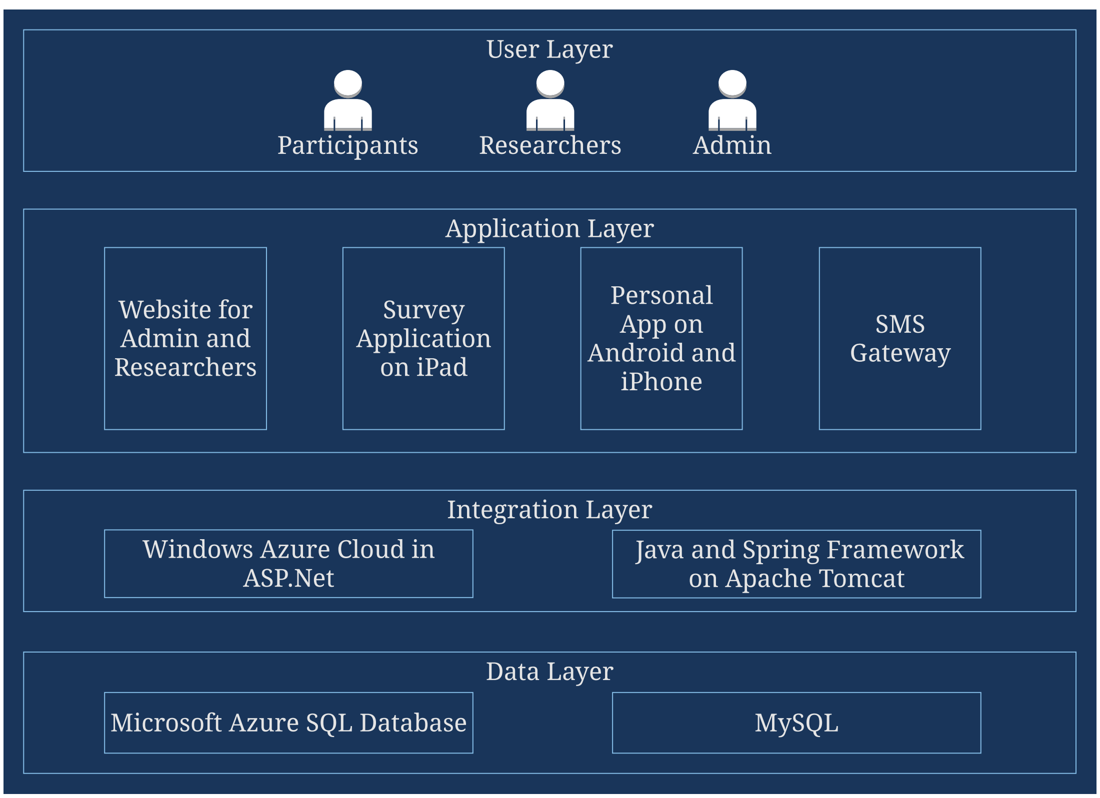

Figure 2.1: General Architecture of the Solution System

as well as applications. Web services help us communicate with the database and works as a wrapper of the database. Data can be retrieved from the database through these web services.

The application layer provides interfaces (different mobile applications, web pages, etc.) that can access, write and read data from the system through this layer. This type of structure helps the system to be simple to access from the users perspective and hides the complexity of the data queries in the underneath layers. Figure 2.1 shows the architecture of the system.

2.1.2 Flow of the System

There are two kinds of end users in our system, direct and indirect users. Direct users use the mobile devices directly and communicate with the system, whereas indirect users take help from direct users (affiliated with the

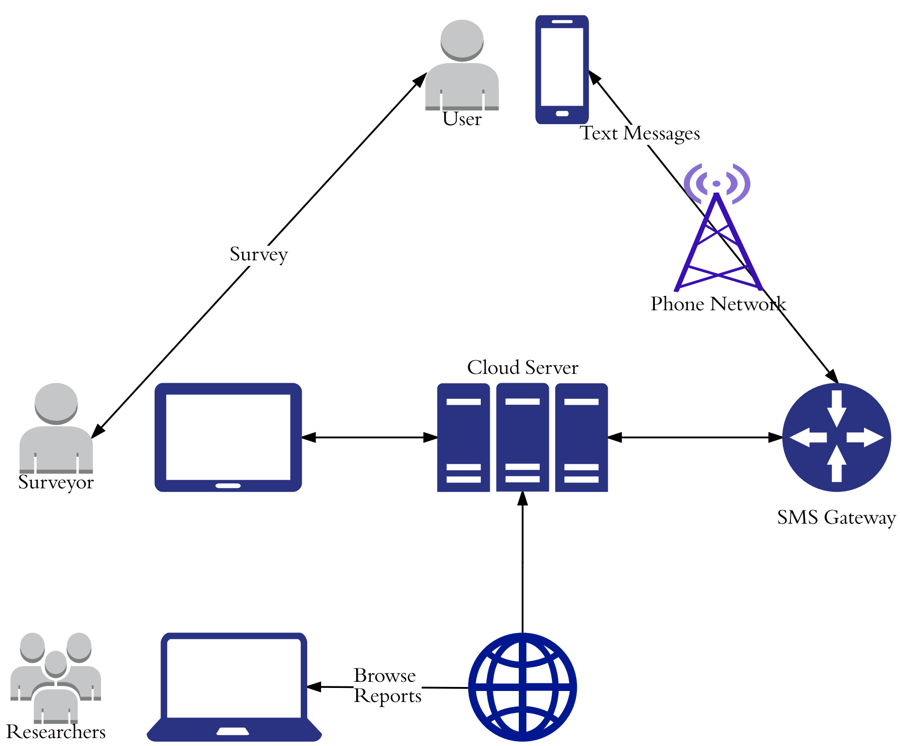

Figure 2.2: General Flow Diagram of the Solution System

research/healthcare services). Both types of users use the mobile device to connect to the system. Data is captured from different sensors and manual input method. The request is made via a wireless network to the server. The server responds with the necessary info. The conversation can go on for several iterations.

The server stores the data acquired from the end users in the database. The server makes adjustments to the settings for the specific user accordingly. The data is stored in the system and can be accessed through the web by the researchers and admins. There are different levels of access so that data are not misused. Figure 2.2 shows the general flow diagram of the system.

2.2 Data Analysis Techniques

For pain level detection, we plan to use several regression methods and some classification methods on the symptom data. These include SVM, Tree, and kNN too. For the image data, we use eigenfaces. We plan to use SVM and angular distance to check similarity for these images and explore other methods.

CHAPTER 3

MHEALTH INTERVENTION FOR SMOKING CESSATION

3.1 Introduction

The prevalence of tobacco dependence in the United States (US) remains alarming. Invariably, smoke-related health problems are the leading preventable causes of death in the US. Research has shown that a culturally tailored cessation counseling program can help reduce smoking and other tobacco usages. We present a mobile health (mHealth) solution that leverages the Short Message Service (SMS) or text messaging feature of mobile devices to motivate behavior change among tobacco users. Our approach implements the theory of planned behavior (TPB) and a phase-based framework. We make contributions to improving previous mHealth intervention approaches by delivering personalized and evidence-based motivational SMS messages to participants. Our solution implements machine learning algorithms that take the participants' demographic profiles and previous smoking behavior into account. In this chapter, we also discuss our evaluation and the observation of our system's performance.

Smoking cigarettes, pipes, and cigars lead to several types of health-related problems including lung cancer and heart diseases [19]. According to the US Center for Disease Control and Prevention (CDC) [19], smoke-related health issues account for more deaths than the aggregate of drug abuse, suicide, motor accidents, murder, and AIDS. About 500,000 people die each year from firsthand or secondhand smoking. Smoking cessation and the avoidance of secondhand smoking is a definite way to reduce the risk of smoke-related health problems. This epidemic can be curtailed by using effective methods to influence behavior change among tobacco users.

Several intervention techniques can be used to treat smoking cessation. In some instances, medicinal approaches, including nicotine patches and other types of nicotine replacement therapy, can be used to control the issue. Personal counseling is another popular method for smoking cessation intervention. Our proposed intervention strategy incorporates a phase-based model that makes use of the theory of planned behavior to influence behavior change towards smoking cessation. Our solution logs the demographic information of the smoking cessation program participants in addition to their self-annotated smoking behavior. We proposed the use of an unsupervised machine learning algorithm to identify patterns in the mined data. The selection of personalized SMS messages is consequently driven by the evidence gathered for SMS messages that are known to positively influence tobacco use patterns for the profile segment to which the targeted user belongs.

3.2 Motivation

With tobacco dependence noted as the leading preventable cause of death in the US [65], we sought to use our proposed intervention strategy to drive down tobacco use in communities that have a high smoking prevalence rate. Our solution was used as part of a smoking dependence study tailored for Native American communities in South Dakota. The prevalence of tobacco dependence among the Northern Plains Native American community, in comparison with other communities in the United States (US), remains very alarming.

In general, Native Americans have the highest percentage of tobacco dependence (31.4%) in comparison with other ethnicities in the US [75]. Notably, smoking prevalence among Native Americans in the Northern Plains of South Dakota is approximately 44.2% [40]. Smoke-related health problems account for about 443,000 deaths or 20% of all deaths recorded annually in the US [75]. By driving down tobacco dependence among the participants in our study, we expect to positively influence tobacco-related mortality in the target communities. More specifically, the application of this intervention strategy aimed to:

- Measure factors that predict smoking behaviors among Northern Plains American Indians
- Identify issues and risk factors related to smoking persistence and high relapse behaviors, regardless of knowledge about smoking hazards, among Northern Plains American Indians
- Using the theory of planned behavior, develop and adapt existing tobacco cessation interventions for use with adult Northern Plains American Indians who smoke cigarettes daily.

The outcome data also revealed predictors of intention to quit smoking, successful quit attempts, and relapses. Other social cognitive variables that ensure initial quit attempts and methods that translate into longer-term abstinence were identified. Results show a significant impact on tobacco use among Northern Plains American Indians while providing insight into effective cessation interventions for this population.

3.3 Related Works

Baker et al. [9] presented an effective phase-based framework that divides the cessation procedure into four major phases. These phases include motivation, pre-cessation, cessation, and maintenance. Raw et al. [69] proposed some recommendations and guidelines for curbing smoking dependence in healthcare. In that article, there are some useful recommendations for healthcare professionals, primary care teams and smoking cessation specialists. Some of the most useful recommendations include: assessing the status of the smoker, advising and assisting the smoker to quit, recommending nicotine replacement therapy, supporting, encouraging and training the participant with coping skills.

Schlam and Baker [75] elaborated this model with the inclusion of an initiation stage along with a cessation stage and a relapse recovery initiation stage. They also showed that though about 70% of the smokers in their study may not have been ready to quit within a specified period, more than 50% of them were open to going through a motivational phase that might lead to an intervention.

Free et al. [40] discussed and reviewed the effectiveness of mHealth based behavior change and disease management interventions. They concluded that the text messaging intervention showed improved results and should be included in smoking cessation methods. We believe that a well-trained recommender engine for creating personalized SMS messages will yield even better results faster. Whittaker et al. [88] evaluated mobile phone-based interventions for smoking cessation and concluded that using a mobile phone for intervention increased the probability of long-term smoking cessation. They analyzed five different methods that studied the effect of using a mobile phone for smoking cessation to arrive at that conclusion. This proves to be an improvement on their previous findings that suggested that there is no long-term effect of using the mobile phone on smoking cessation. We believe our proposed approach will prove to be more effective for long-term behavior change toward cessation.

Ajzen [5] proposed the theory of planned behavior (TPB) to find the relationship between behavior and attitude. In this theory, he proclaims that attitudes toward the behavior, subjective norms, perceived behavioral control, etc. caused significant changes in actual behavior. The author introduced several concepts such as behavioral beliefs (the beliefs which influence the attitude towards a behavior), normative beliefs (which influences the subjective norms) and control beliefs (which is the basis of perceived behavioral control) as different key factors for the creation of actual behavior. In short, a user's behavior depends on how he or she wants to behave, what the surroundings expect of him or her, how motivated he or she is about that specific behavior and what behavioral controls and abilities he has. The author also provided a mathematical model showing how these components relate to each other.

Norman et al. [64] tried to apply the TPB to predict a smoker's intention and behavior. They were able to predict correctly the intention and attempts to quit with behavioral intentions, but they were not able to predict the length of abstinence among the smokers. They indicated the necessity to identify the social cognitive variables to predict this.

3.4 System Characteristics

Some of the key components of our mHealth intervention approach include short message service (SMS), machine learning recommender algorithms, mHealth, the theory of planned behavior, and phase-based frameworks.

3.4.1 Short Message Service (SMS)

SMS, or text messaging, offers cellphone users the ability to send and receive short and instant messages. Participants in the intervention study were furnished with low-cost mobile phones. Each mobile device was equipped with text messaging capabilities. The SMS feature is the most widely used mobile data service today [89]. 74% of all mobile phone users worldwide, about 2.4 billion people, use the SMS feature. It is less expensive in comparison to audio and video messaging services. SMS is very popular for sending digital information. The choice of this medium of communication between the participants and our automated SMS gateway was partly based on an interest in establishing a low-cost mobile health intervention that our participants could afford to use.

3.4.2 Machine Learning Recommender Algorithms

Our solution sought to deliver personalized and evidence-based motivational SMS messages to the program participants through the implementation of machine learning algorithms that take the participants' demographic profiles and previous behaviors into account. A user-based recommender engine algorithm was used to select the best-fit message from a list of motivational messages stored in our database, instead of simply selecting random SMS messages that may or may not be influential for a given scenario. The algorithm explores the notion of sameness or the Euclidean Distance similarity metric between users who have previously indicated that they realized a motivational effect after receiving a given group of motivational SMS messages. The more similar a given user is to another participant who previously had success with a given set of messages, the more heavily the previous user's set of motivational messages is weighted for selection. Recommender algorithms including Pearson Correlation Similarity, Euclidean Distance Similarity, and Log Likelihood Similarity were considered for this implementation.

3.4.3 mHealth

Mobile Health (mHealth) represents the advancing subclass of digital health solutions that apply mobile phone technologies in the healthcare industry. With the rising adoption of mobile devices, mHealth presents a very convenient way to reach large groups with healthcare and wellbeing services. Mobile devices are quickly becoming the most used medium for two-way communication. Given the vast user base of mobile devices, we deemed it very important to select mobile devices as an effective means of communication for our healthcare intervention. Additionally, mHealth technologies are not limited to smartphones. Various mobile devices of varying forms can be used in mHealth solutions, including tablets, patient-monitoring devices, MP3 players and more. In our intervention approach, we leverage SMS for delivering motivational messages to program participants.

3.4.4 Phase-Based Framework

A phase-based framework was used for the target study to help understand various behavior patterns during various phases of the intervention. The integration of this framework along with the TPB presents an appropriate treatment and psychosocial intervention that can be assessed at each stage of the smoking cessation process. Sensitive outcome measures and the efficacy of the intervention were identified through the fusion of the aforementioned framework and theory. A better understanding of how interventions influence behavior at each phase aided the development of an optimal smoking cessation program.

Participants in the cessation program were evaluated during several phases. The first couple of phases were focused on motivating the participant to quit smoking. This phase can have an infinite length. If a participant became motivated, he or she proceeded to a pre-cessation phase. During pre-cessation, the participant identified a future date for quitting. The cessation phase commenced when the participant was ready to deliver on the promised target date. During the cessation phase, the participant might need medical help, such as access to nicotine patches, etc. After the cessation phase was complete, the participant went through the maintenance phase. The phase-based framework ensured that the different stages of the cessation process were well understood and adequate preventive and supportive measures were taken according to the needs of the phase in question.

3.5 Implementation Details

We designed and implemented an SMS solution for interacting with smoking cessation program participants in an effort to influence behavior change. Our implementation of the SMS intervention solution is described below.

3.5.1 Functional and Non-Functional Features

The system generated motivational text messages and sent these automated text messages to participants. The system also had conversational two-way communications with participants by interpreting certain pre-programmed keywords including: ″slip,″ ″crave,″ ″signup,″ etc. The solution made use of a secure web site and web services to register users and display insights into the user′s progress in the program.

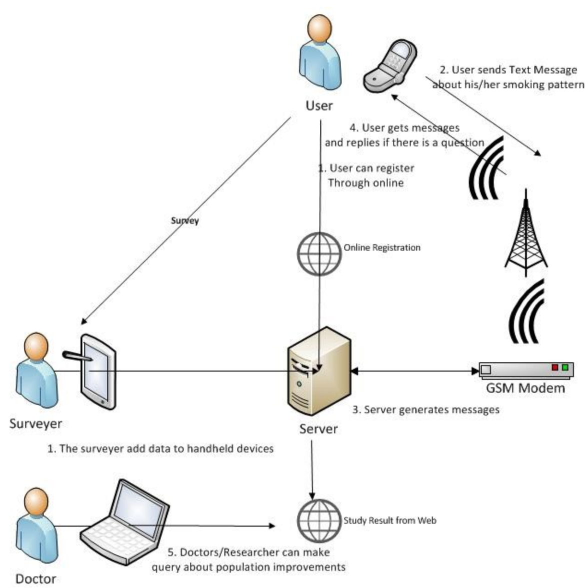

Figure 3.1: Data Flow Diagram

The system also provided support for administrators to build surveys dynamically through a web administration portal. These surveys were used as evaluation vehicles for testing the efficacy of the smoking cessation intervention by constructing an engine used for building and administering surveys across multiple mobile platforms including Windows 8 and iOS. Our dynamic survey engine allowed the program investigators to easily build, customize and administer surveys through tablets and smartphones on-the-fly while exposing an extensible application programming interface (API) to allow future applications to leverage the survey engine for various evaluation tasks.

The feedback signals collected from the evaluation tool were successively fed into a Health Insurance Portability and Accountability Act (HIPAA)-compliant cloud-based data store and, in turn, helped to improve the efficacy of the evidence-based algorithms used in the mHealth SMS intervention. The surveys collected demographic information regarding participants who were looking to eliminate their dependence on tobacco. Demographic information included education, employment, gender, age, and more. The system also collected intent of enrollment, which may have included the amount of daily tobacco use, a target plan for quitting, and more. The system stored all the recorded information in a secure database system so that the end users' anonymity was protected.

We implemented a custom SMS gateway using an Android-based smartphone. The SMS gateway interacted with our cloud-hosted data store through a web service API.

3.5.2 Solution Architecture

As illustrated in Figure 3.2, our solution architecture features a cloud-hosted SQL Azure data store (at the Data Tier) with a service oriented architecture-based (SOA) integration tier that consists of multiple WCF web services that broker all interactions from the application tier to the data tier. Our application tier consists of a participant web site as well as an administration web portal, a number of cross-platform native mobile apps for conducting surveys, and an SMS gateway.

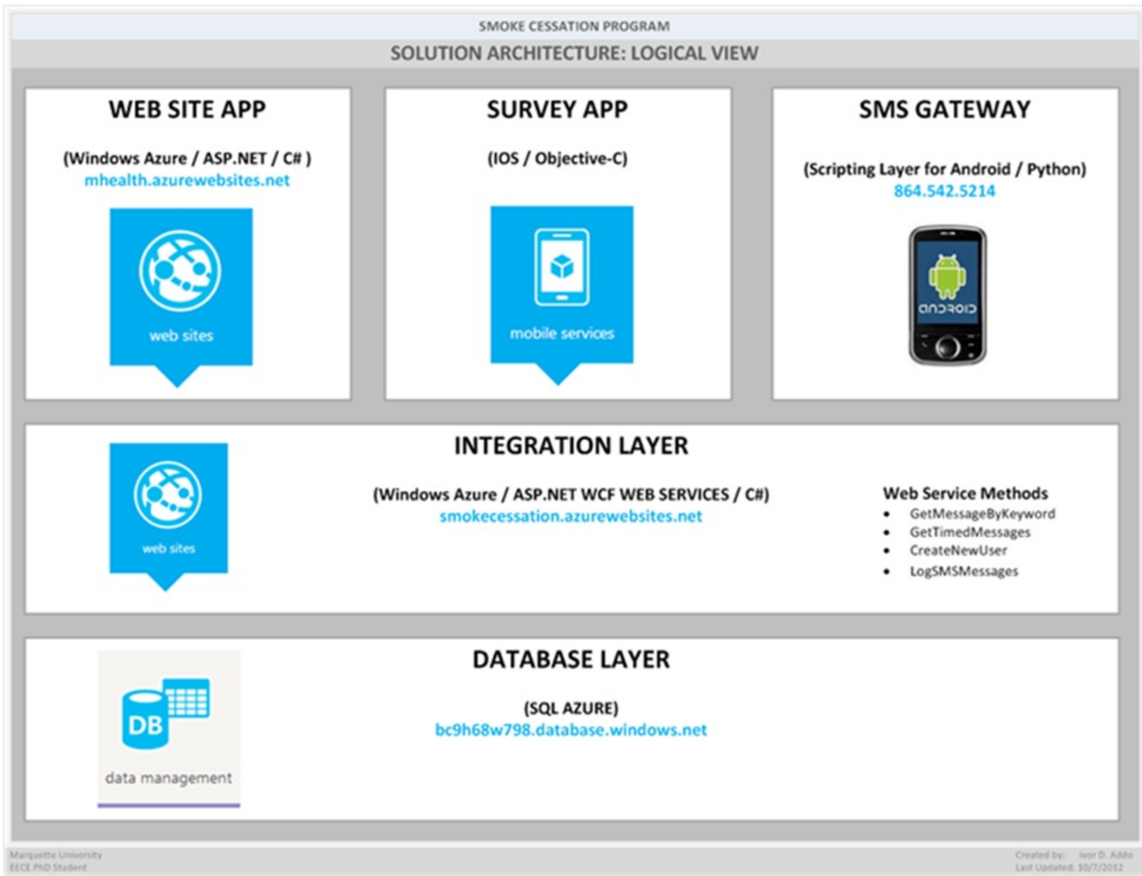

Figure 3.2: Logical View of the Solution Architecture

3.5.3 Motivational Question Selection

In implementing the phase-based framework, we designed various motivational messages that were tailored to the known challenges of the intervention phase in question [69]. Table 3.1 illustrates some of the tailored messages stored in the database. Subsequently, the recommender engine was used to select the best-fit message to be sent to the participant as a response.

Table 3.1: Sample Motivational Messages

Phase	Challenges	Text messages
Motivation	Low motivation	It's never too late to quit smoking; you deserve to be free from tobacco.
	High dependence	Did you know that the single largest preventable cause of disease and premature death is smoking?
	Lack of support	Let your friends and family know that you are trying to quit; they can help you stay motivated.
Precessation	Withdrawal and craving	The first few days will be the hardest, try to keep your mind off smoking by doing something fun.
	Coping Skill practice	Why don't you go for a walk? Distracting yourself can help curb the craving.
Cessation	Withdrawal and craving	When a craving hits, try chewing some gum or a healthy snack like carrot sticks or celery, it may help to keep your mouth busy.
	Lapses	Just because you slipped it doesn't mean you failed. It's worth it to not give up, try again.
Maintenance	Lapses/Relapses	It's okay if you slip, most smokers take between 8 and 11 attempts to quit, don't give up.
	Decline in motivation	After 2 days of not smoking your ability to taste and smell have improved.
	Non-adherence	Are you noticing that you can breathe more easily? After 3 days of not smoking your lung capacity has increased.

3.5.4 Development and Deployment

For the initial SMS gateway component, we built a Python script that ran on an Android device and interacted with our cloud service API. In our later version, we developed an android application that worked as the text messaging gateway. ASP.NET MVC, C#, HTML5, jQuery, and CSS were leveraged for building the mobile-responsive web site. The web service API was built using Microsoft's WCF web service templates. We used SQL Azure as our data store solution. All web interface and database components were hosted on the Microsoft Windows Azure cloud service. The survey apps were built for iOS iPad and Windows 8 Surface tablets. Apache Mahout was leveraged for building a scalable recommender engine.

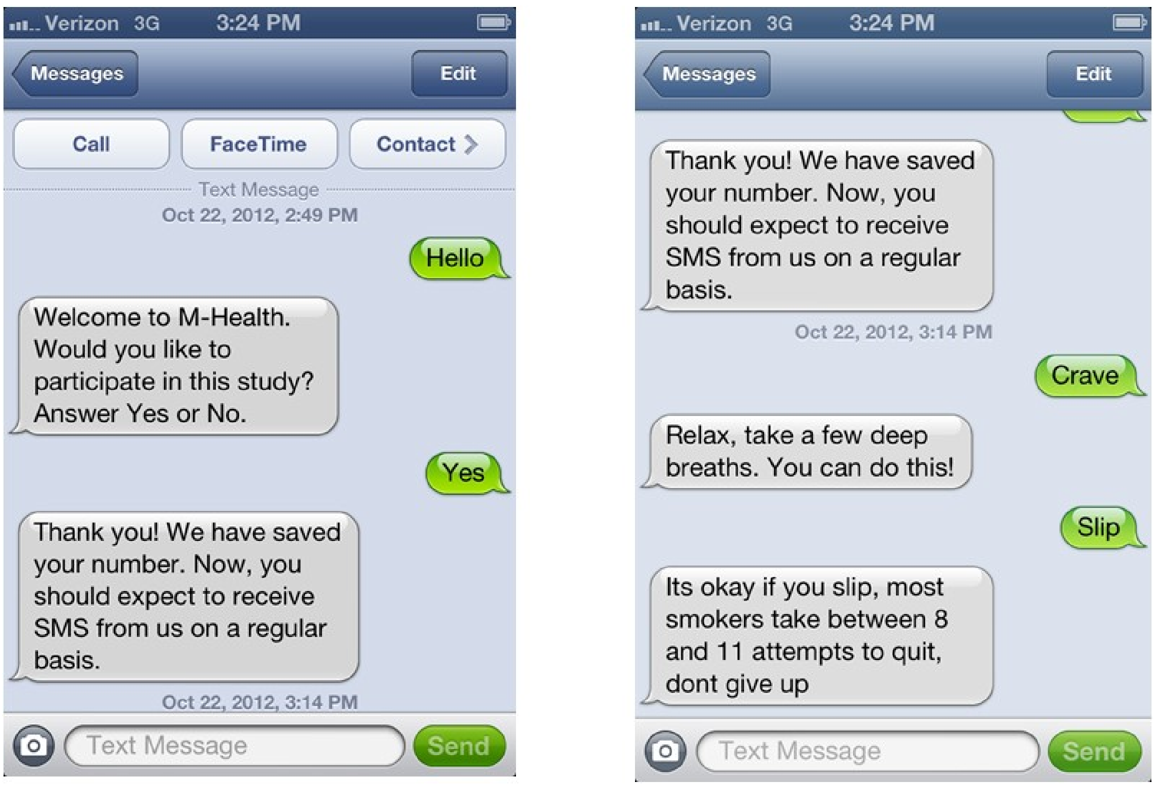

Figure 3.3: Automated Messages for User Enrollment

3.6 Evaluation

To evaluate our mHealth SMS intervention approach, we conducted the following tests:

- Evaluate the mean down time
- Evaluate the usability of the various solutions
- Evaluate Efficacy of the Intervention Approach

3.6.1 Mean Down Time

Our solution system had a very low mean down time. In the very beginning of development, we noticed that there were drops in bulk text messaging due to android send limit. We distributed the outgoing messages over a time to counter that issue. We also noticed system crashed due to data and log load in the early phases. We introduced regular system restart and archived the log files to stop those crashes. After those changes, there were no system down times.

3.6.2 Usability of the System

Our preliminary usability testing revealed that 90% of our 10 testers favored the personalized messages, while one user was indifferent to receiving a personalized message versus a randomly selected message of potentially less relevance. Text messaging communication was very easy for the participants to understand and they replied correctly on their morning query messages.

3.6.3 Efficacy of the mHealth Intervention Approach

To evaluate the efficacy of the mHealth intervention approach, we conducted periodic surveys during various visitation sessions throughout the intervention phases outlined in the phase-based framework discussed earlier.

American Indian participants in the Northern Plains of South Dakota were self-identified and self-referred after hearing or reading promotions disseminated throughout the target reservations. Participants who could not afford cellphones were furnished with mobile devices. The study lasted for about three years in a bid to evaluate the effect of this approach in fostering long-term behavior change and reducing the associated health risks. There were 256 participants in the study.

In addition, this study employed traditional cessation and pre-cessation counseling techniques as well as nicotine replacement therapy for a cross-section of the targeted community population. The efficacy of the traditional in-person cessation counseling approach in relation to the mHealth approach was determined to test our hypothesis around the superiority of the mHealth approach.

Participants were required to self-report their progress in the cessation program on a regular basis. The self-reported user behavior information was logged and utilized for continually improving the SMS message recommender engine. Even so, the data logs were mined to gain insight into the effectiveness of the mHealth approach in engendering behavior change. A cross-section of participants who engaged in the mHealth intervention were presented with evidence-inspired personalized messages while the other group were presented with random messages. We used the results of this multivariate testing approach to determine the efficacy of personalized motivational SMS messages in comparison with randomly selected messages from the motivational message database.

mHealth intervention were also differentiated by the level of intensity. Different groups received different numbers of motivational text messages. Analyzing the results of this multivariate testing approach helped us determine the efficacy of personalized motivational SMS messages.

Our periodic surveys showed that more than 90% the participants agreed or strongly agreed throughout eleven surveys that text messaging was helpful for them to quit smoking. We also did an analysis of carbon monoxide levels in exhaled breath to check their progress. Our analysis showed that there were significant decreases in the carbon monoxide levels in the participants during the study. This showed a direct physiological impact of the intervention system.

3.7 Conclusion

Our findings suggest that there are opportunities to deliver a personalized mHealth solution that will be welcome as a suitable intervention strategy for motivating smokers towards their goal of smoking cessation. We described our implementation of the technology solution and offered insight into how the physiotherapy theory and framework components were implemented in this approach. We anticipate that our contributions to applying machine learning algorithms to infuse a level of intelligence in the selection of motivational SMS messages will create a blueprint for future work in this area. We conducted an exhaustive evaluation exercise and shared our insights into the efficacy of the mHealth intervention approach in comparison with other smoking cessation strategies.

3.8 Acknowledgment

We are grateful to Regis Rutarindwa, Heather Bort and Brian Truka for their contributions in developing the initial prototype of the solution. This project was partially funded by the National Institutes for Health (NIH) and was used for a study of smoking dependence in Native American communities in the Northern Plains of South Dakota, US.

CHAPTER 4

MHEALTH MOTIVATION SYSTEM FOR PHYSICAL ACTIVITY

4.1 Introduction

It is necessary for a cancer survivor to have good health behaviors. Essential exercise and healthy diet are helpful to decrease the risk of recurrence of the disease and the development of new cancer types. People from low socioeconomic status are more likely to participate in risky health behaviors and have a higher chance of recurrence of cancer. It is essential to have a motivational system for cancer survivors that motivates them to perform regular physical activities. In this article, we discuss the development of an mHealth system that aimed to increase physical activity in a Native American population with culturally appropriate motivational text and video messages. The system also included a regular e-journal to help monitor and maintain proper health-care. We also analyze the pilot data to evaluate the usability and the effectiveness of the system.

Cancer survival is a hard and long journey, and it does not merely end with being cured. Due to the advancement of modern research as well as improvements in the health sector, more and more people are being cured of cancer. Cancer survival has its own physiological and psychological side effects, a few of them being weight loss, fatigue, nausea, depression, etc.[13][24] Cancer survivors have a higher chance of developing secondary cancers and other chronic diseases [15][33]. There is a higher chance of decrease in physical and physiological quality of life among these patients. Recurrence is also related to body weight. Studies find that being overweight increases the chance of recurrence and decreases the likelihood of survival [90][17]. Lack of physical activity is related to colon [91], breast [41] and endometrial cancers [61].

Most of these can be kept in check with the aid of various physical activities and regular exercises. About one third of cancer is preventable by having a healthy lifestyle, which includes regular physical activities and a balanced diet [33]. Studies conducted on groups of cancer survivors have shown that regular physical exercise has a positive impact on the overall physical performance of these target groups. Such an example is the improvement of walking speed and distance [30] [29] of a cancer survivor group with the help of physical exercise. Exercise leads to the improvement of different vital organs (heart, lungs, etc.). It also reduces fatigue and improves quality of life of a survivor. Research has found that post-cancer treatment physical activity is significant as this decreases the recurrence rates and increases overall survival rates [90][17][57].

Considering these issues, we present a culturally tailored intervention system for physical activity among cancer survivors that focuses on a Native American population from the Northern Plains. In this chapter, we describe our motivation, related research, development, and our findings.

4.2 Motivation

Native American people have lower cancer survival rate than other US ethnic and minority groups, especially in the Northern Plains [77][28]. Several reasons lead to this, including lack of access to cancer treatment, inadequacy of health insurance, and lack of transportation and services. Because of late diagnosis of the disease and fewer treatment options, several side effects occur and many times ends in patient death.

A significant factor regarding the well-being of a cancer survivor is their socioeconomic status. The quality of healthcare and life also depends on a person's socioeconomic status. People with low income have trouble getting a balanced meal. They also do not have the motivation to spend time participating in physical activities. It should also be noted that people's behaviors are affected by their culture, and while developing an intervention system, it is therefore necessary to include cultural components in the intervention process.

Our goal was to develop a motivational system for cancer survivors to motivate them to become more active physically. To achieve that goal, we planned the following tasks:

- Develop a cell phone application which motivates a person to become more active physically and also works as a self-submitted e-journal
- Develop a text message system for motivation
- Develop a data collection/survey application

4.3 Related Works

Mobile phone text messaging is widely used as a potentially powerful tool for behavior change because of its availability, low-cost, efficiency, convenience, and less intrusiveness compared with a mobile phone call [21]. Various text-message based intervention systems and mobile applications [58][7] have been built for reducing the risk of various diseases like Diabetes [86][66], for smoking cessation[87][50] and also to increase physical activity [54][51]. Many research studies have been conducted to show how behavior change can reduce the risk of several diseases [7] as well as on the effectiveness of text-messages and video-messages for behavior change [21][54].

Phillip et al. [7] conducted an interventional randomized controlled trial where treatment group was provided with a bespoke "Gray Matters" mobile phone application designed to encourage and facilitate behavior change. The result showed that the ubiquitous nature of the mobile phone excelled as a delivery platform for the intervention, enabling the dissemination of educational intervention material while simultaneously monitoring and encouraging positive behavior change, resulting in desirable clinical effects.

Pamela et al.[54] did a pilot study to assess whether a text message intervention would increase physical activity in African American adults. The text messages provided strategies for increasing physical activity. They were based on constructs of the Health Belief Model and the Information-Motivation-Behavioral Skills Model. The results of this pilot study suggest that text messaging may be a useful method for providing options for motivating individuals to increase physical activity.

Robyn Whittaker et al. [87] carried out a randomized controlled trial to assess the effectiveness of a multimedia mobile phone intervention for smoking cessation. The intervention group received an automated package of video and text messages over six months that was tailored to self-selected quit date, role model, and timing of messages. Feedback from participants indicated that the support provided by the video role models was essential and appreciated.

Chandra et al. [66] explained the development and feasibility of an intervention system using text-messaging and interactive voice response for low-income diverse adults who were suffering from diabetes. The types of challenges encountered in design were related to providing text message content with valued information and support that engages patients. The design process also highlighted the value of obtaining mixed methods data to provide insight into legitimate versus illegitimate missing data, patterns of use, and subjective user experiences.

Brian [83][11] discussed how to design text message behavioral interventions and what limitations exist while using text-messages for behavioral interventions. According to him, the development process can be divided into six steps: 1.) needs assessment; 2.) specifying performance and change objectives; 3.) selecting theory-based intervention methods and practical applications; 4.) designing and organizing the intervention; 5.) determining adoption and implementation plans, and; 6.) generating an evaluation plan.

The Multiphase Optimization Strategy developed by Collins et al. [23] offers a guide to more efficient behavioral program development. It consists of a screening phase, in which intervention components are efficiently identified for selection for inclusion, a refining phase, in which the selected components are fine-tuned, and a confirming phase, in which the optimized intervention is evaluated in a standard randomized confirmatory trial. Finally, Mohr et al. [59] published an integrated conceptual and technological framework for eHealth interventions that maps behavioral intervention aims to technological strategies.

4.4 Our Approach

In this section, we will discuss the architecture, the functionalities, the development and the deployment of the system. We will also discuss about the different components in the solution system.

4.4.1 Architecture

The architecture of the solution system can be described through the four layers: the user layer, application layer, integration layer and data layer. Let us discuss the layers from a bottom-up approach. On the very bottom, we have the data layer. In our system, the data layer is implemented by a MySQL database server. This server runs on a virtual machine created by the Microsoft Azure portal. On top of the data layer, we have the integration layer. The primary server runs on Apache Tomcat that uses Java and Spring Frameworks. In the application layer, we have several components. There is a website for administrator and researchers to use, SMS gateway for text messaging, iPad application for periodic surveys and Android application for activity tracking and e-journal used by individual participants. Finally, in the user layer, we have the participants, the researchers and the administrators of the system.

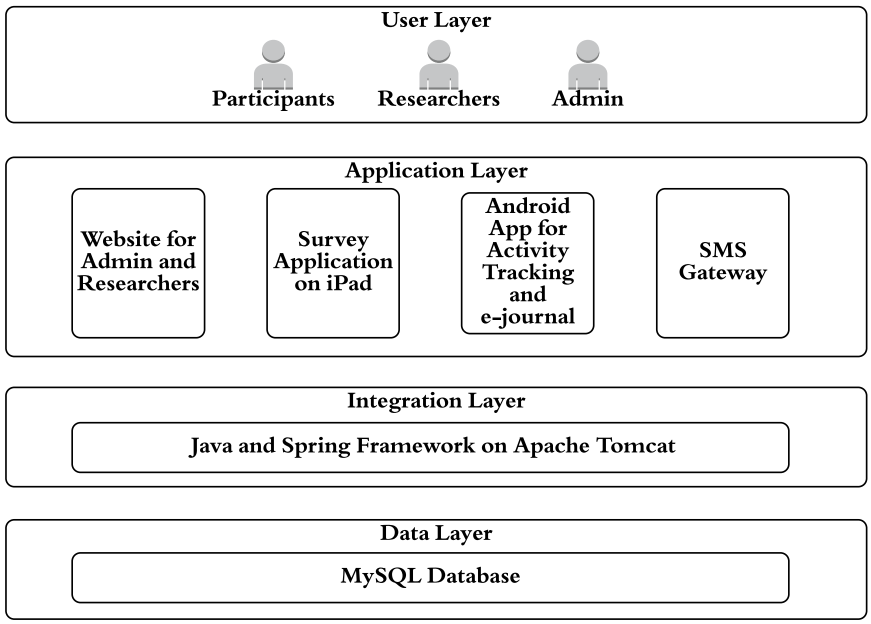

Figure 4.1: Architecture diagram of the solution system

4.4.2 Functionalities

The iPad app was used for participant enrollment and biweekly in-person surveys. The Community Research Representatives (CRRs) used the iPad application to enroll the participant and collect baseline and biweekly survey data from them. Collected data was sent to the primary server and then stored in the database.

The website for administrators and researchers is used for multiple purposes. The administrators use this to update participants' information. It is also used to add text and video messages that are culturally tailored. The website is also used by the researchers to check the progress and status of the participants.

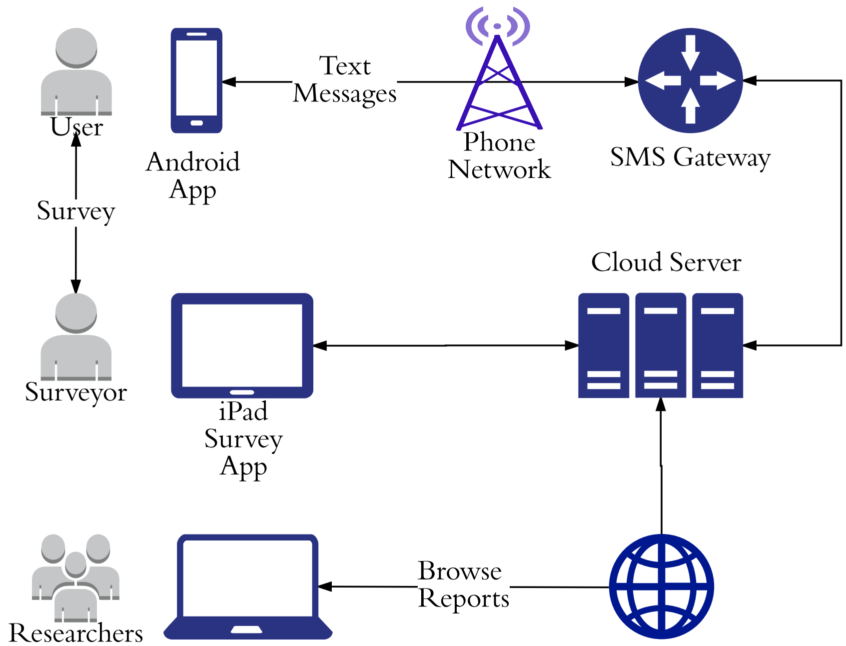

Figure 4.2: Data flow diagram of the solution system

To ensure seamless text message transactions, we utilized a third party text messaging gateway system, Clickatell. Anytime a text or video message was required to be sent to a participant, the primary server sent the message to Clickatell gateway, and then it was sent to the appropriate person. The server itself made the selection of the text messages. Every day, at four different times, the server created the outgoing text message list. To ensure each participant was getting the appropriate messages, it looked into the participants preferred settings, their current phase of the program, etc. to generate a pool of text messages. From that pool, a single message was selected for each participant. Then the message was sent to the text message gateway and from there, to the participant.

The final application layer component was the personal android application. There are several functionalities of the application. With this application, the participants submitted their daily and weekly e-journal. These journals were composed of sets of questions regarding their current physical activities and their well-being for the past week. The application also included tutorial videos for the application. There was also a settings menu, where the participants updated their text message settings and preferences.

4.4.3 Text/Video message generation

With the help of our research groups expertise in developing mHealth tools and culturally appropriate behavior and community-based research, we developed a low-cost and efficient text message system. In the system, the participants received four daily text/video messages. The messages were sent to them at 6 AM, 11 AM, 3 PM, and 6 PM. These messages included motivational quotes and specific strategies related to physical activity. The video messages were created from filmed interviews of Native American cancer survivors. These survivors shared their experiences and stories regarding their motivation for physical activity. The research team collected culturally significant motivating stories and converted them into text messages of 160 or fewer characters.

For the video messages, our team decided to send the links of the video messages as text messages. The output of this method decreased the data traffic for the participants, and helped solve network access problems for participants. The pilot study was set up in a rural area, where connectivity to the wireless network was sometimes poor. With our setup, it was possible for them to find a reliable wireless or wi-fi network and then watch the videos in their preferred time.

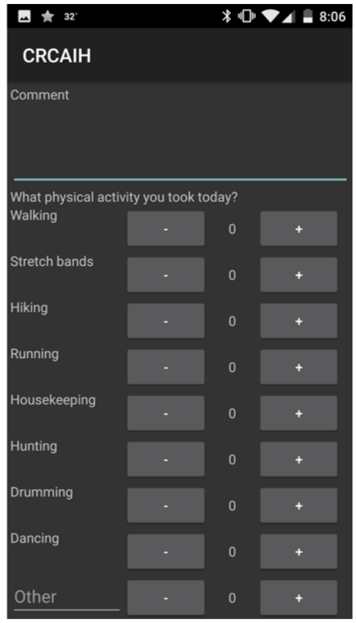

Figure 4.3: Daily e-Journal

4.4.4 e-Journal

The e-Journal was another important component of the system. Many cancer survivor websites and research groups encourage keeping a journal to track the persons daily experience and improve their quality of life. In our system, we used two separate journals: the daily journal and weekly journal. Using these journals, the participants input their daily physical activities and any concerns they had. The daily journal included questions designed to find out how the person was feeling on that day, whether they were able to do everything they wanted or not, how long they were able to do those works and if their emotional state was well or not. For the weekly journal, there were two types of questions. In one set, there were questions about their overall physical activity, its effects, and their overall feelings during that period. In the other set, there were questions regarding the app, the text messages, the e-Journal and their overall performance from the participants viewpoint.

Figure 4.4: Daily e-Journal 2

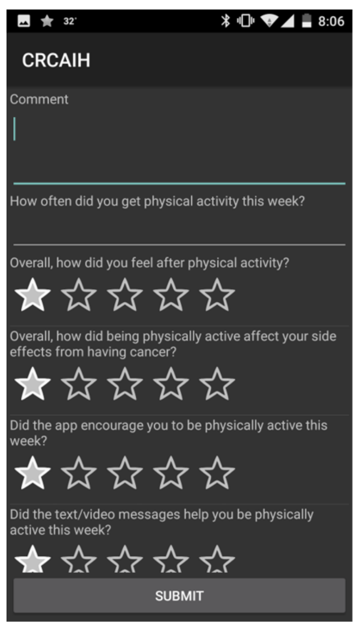

Figure 4.5: Weekly e-Journal

4.4.5 Periodic Survey

Another essential component of the system was the periodic survey. The first and baseline survey also functioned as the enrollment process. During enrollment using the iPad application, the CRRs informed the participants with the study overview and the aims of the system. If all the eligibility criteria were met and none of the exclusion criteria were selected, the participant was guided to the consent screen. After agreeing with the consent information, the participant was enrolled, and the participant answered the questions for their baseline visit. The study continued for about three months, and there were bi-weekly surveys. The participants visited the health center, and their assigned CRRs met with them to collect information regarding their progress and health status. The questions included queries about their current health status, and if there were any issues in the past two weeks.

Another essential component of the system is the periodic survey. The first and baseline survey also worked as the enrollment process. During enrollment, the CRRs informed the participants with the study overview and the aims of the system using the iPad application. If all the eligibility criteria were met and none of the exclusion criteria were selected, the participant is guided to the consent screen. After agreeing with the consent information, the participant was enrolled, and the participant answered the questions for their baseline visit. The study went for about three months, and there were bi-weekly surveys. The participants visited the health center, and their assigned CRRs met with them to collect information regarding their progress and health status. The questions included queries about their current health status, and if there were any issues in the past two weeks.

4.4.6 Development and Deployment

The cloud server was deployed in a virtual machine designed by Microsoft Azure portal. The database was designed in a MySQL server. The iPad application was developed in Objective-C with the development tool XCode. The

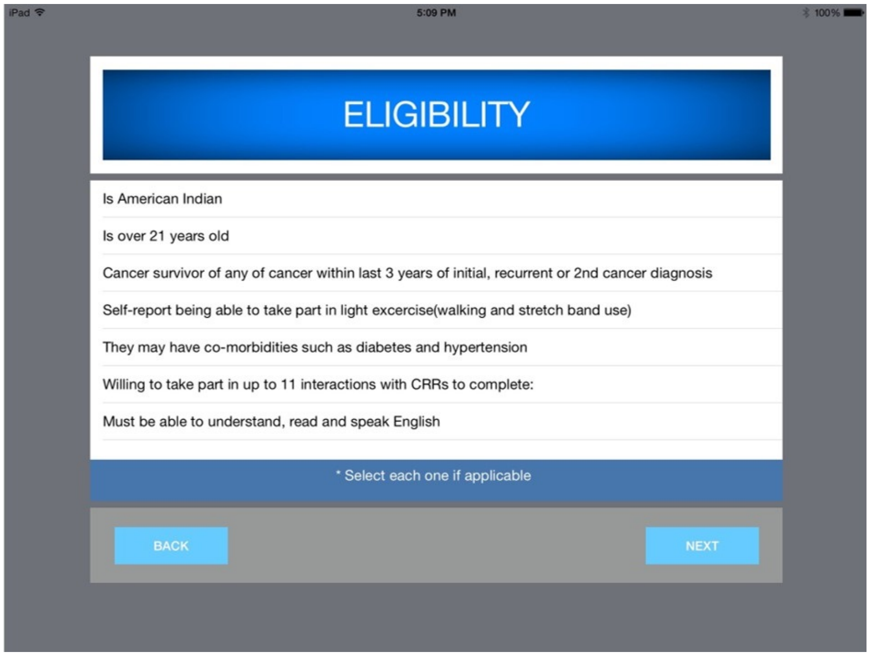

Figure 4.6: Screenshot 1 of survey application

android application was developed in Java with Android Studio. The primary server ran on Apache Tomcat and used Java and Spring frameworks. All the server components were deployed in the cloud.

4.5 Evaluation

We evaluate our intervention system in following methods:

- Mean Down Time
- Usability
- Efficacy

4.5.1 Mean Down Time

The pilot study lasted for about three months. There were seven participants. In our solution, we incorporated a third party text message gateway (Clickatell) to send text messages in bulk. Using a renowned and scalable system ensured that there was no disruption of the system. Other essential server

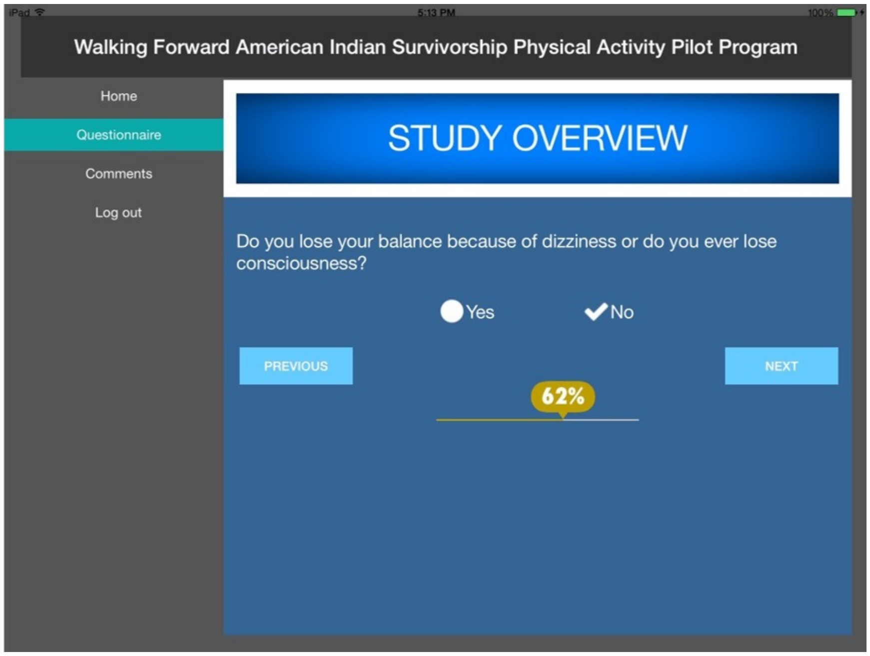

Figure 4.7: Screenshot 2 of survey application

components were the primary server and the MySQL server. They were deployed in a virtual machine created under Microsoft Azure portal, and there was no downtime for the time frame of the study.

4.5.2 Usability

There were several components of the system. They differed in access roles. For example, the administrators used the website; the CRRs used the iPad survey application, and the participant cancer survivors used the android application. These components were accessed according to each user's role. There were no concerns raised by the participants regarding problems using the application. Moreover, there were tutorials provided for the participants about the use methods of the application.

4.5.3 Efficacy

The weekly journal had specific questions about the efficacy of the system. 5 of the participants answered the efficacy questions. Table 4.1 shows the percentage of the replies.

Table 4.1: Efficacy of the system

Question	Percentage agreed
Did the app help to be physically active?	100%
Did text/video messages help to be physically active?	88.89%
Did the eJournal encourage to be physically active?	100%
Overall how satisfied with the system?	68.88%

4.6 Conclusion

In this study, we developed the intervention system with several components. Though the pilot study was small in size regarding participants, as our design is implemented in a scalable platform, it requires little change to implement the whole system for a more substantial population. In the pilot data, it shows that having such a system helped the participants to get motivated for physical activity.

In this chapter, we described the development stages of all the components of our solution system. We explained how each component worked and the communication among them. We also described our initial findings from the pilot data. This system is ready for a larger population, and we believe it will help many cancer survivors by motivating them to be more active physically and improve their quality of life.

CHAPTER 5

COMPARISON OF SPECIALIZED MHEALTH INTERVENTION SYSTEMS

5.1 Introduction

In this chapter, we will discuss the two different text messaging systems that we designed and implemented. The text messaging systems were designed for Smoking Cessation and Physical Activity for Cancer Survivors. There are some differences between the systems.

In the first system, employed in the Smoking Cessation project, the text message server ran on an android device. The android phone with a wireless telephone networks performed the receiving and sending of text messages. Different participants received different numbers and types of text messages according to their study group, progress in the study and their customized settings. Text messaging settings were first selected from periodic surveys. During several survey visits, the participants were asked about their text messaging preferences. At the beginning of each day, the android server gathered the existing participants and sent them a good morning message with a list of options. Upon receiving their response, the text message server sent them periodic text messages according to their preference, their progress in the intervention, and their personalization and customization preferences.

In the second system, employed in the Physical Activity for Cancer Survivor's project, we used the service from Clickatell to send the text messages. The server collected the participant list at a specific time of day and sent the appropriate text messages to the participants. The text messaging service settings could be changed from the user interface of the android application from the individual users.

5.2 Comparison of the systems

In this section, we will compare the two text messaging intervention methods depending on the system structures, flow of the systems and the functionalities of the systems.

5.2.1 System Structure

The architectures of the systems were similar, but there were still some differences. In this subsection, we will discuss the differences between the architectures of the systems.

Smoking Cessation

In the Smoking Cessation System, the bottom tier consisted of the database. The database was an SQL Azure database in the Azure Cloud. The integration layer on Windows Azure cloud sat on top of the data layer. ASP.Net web APIs were hosted in this cloud service, which takes JSON and SOAP XML inputs. This layer communicated with the data layer to make changes in the database and collect information about different participants from the database. Different components of the application layer communicated with the core of the system through this integration layer. For example, the web site component makes it possible for the admins and researchers to access the data according to their role and watch progress and monitor reporting of the participants. The iPad survey applications helped collect data from participants by surveys conducted by the researchers. The system collected their text messaging preferences from these surveys. The text messaging gateway, which is an android application, was also included in this layer. An android application worked as the text messaging server gateway and delivered text messages to the participants. In the user layer, there were the participants, the researchers and the admins, who accessed the system through the application layer according to the access level of their role.

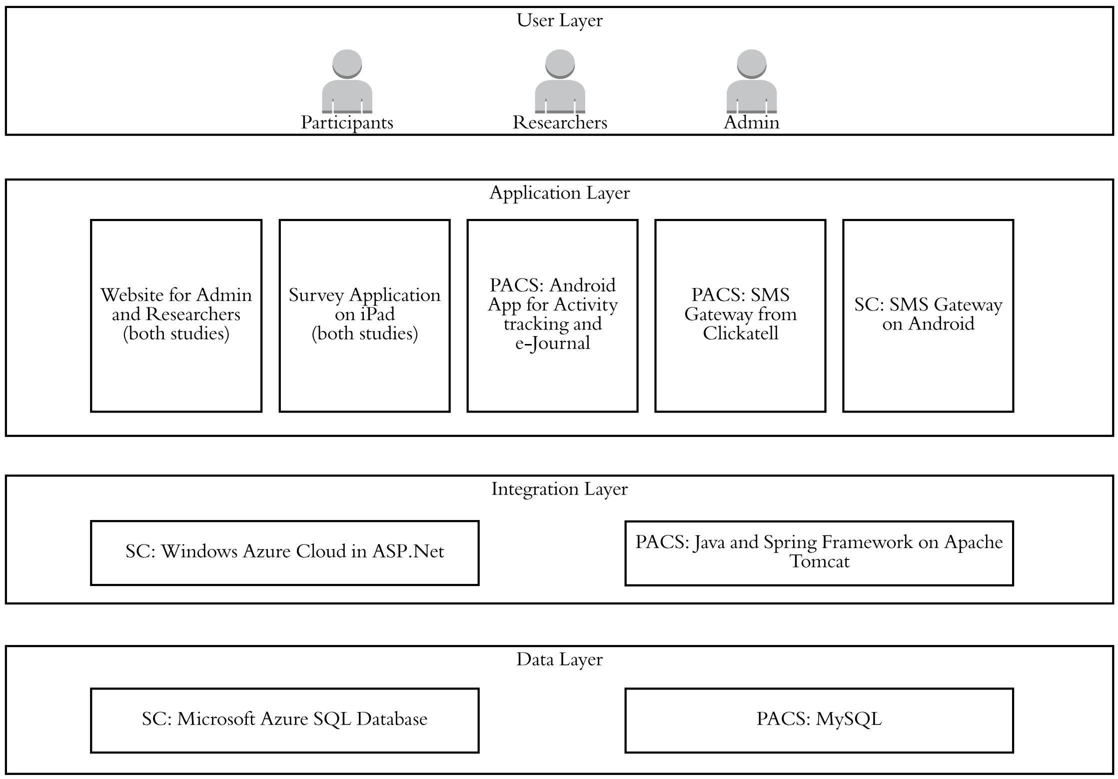

Figure 5.1: Text Message System Architecture

Physical Activity

For the Physical Activity for Cancer Survivors system, the bottom layer was the database, which was stored on a cloud running on a MySQL server in a virtual machine created by Azure portal. On top of that was the integration layer, where the main server was running. The server communicated with the database and collected the participant information and text or video messages. On top of the integration layer was the application layer, which had several components. First, the website, which had admin panel and reporting features. Second, the survey app, which the researchers used to collect data from participants at specified time intervals. An android application collected the physical activity data and was used by participants to submit e-Journal entries. The app also had text message settings, which updated the users preferences in real time. The Clickatell text messaging gateway sent the messages to the user. On top of all these was the user layer, which had all the participants, researchers and admins of the system. They communicated with the whole system using the items from the application layer.

5.2.2 Flow of the System

In this subsection, we will discuss the difference between the data flow of the two systems.

Smoking Cessation

In the smoking cessation system, a participant was added to the system from the baseline survey, which also registered the participant into the system. During visit 2, the participant was assigned a phone to receive text messages. Some text messaging options were also selected during these surveys. The text messaging server sent morning messages to the participant asking for their text messaging settings for that day. Upon receiving their reply, the server changed the settings of that participant for that day and selected a random text message from the pool of messages with the correct setting. Then the android app sent the message to the participant. The sent and received text messages were also stored in the server for future queries. The researchers and the admins accessed this information depending on their role in the system.

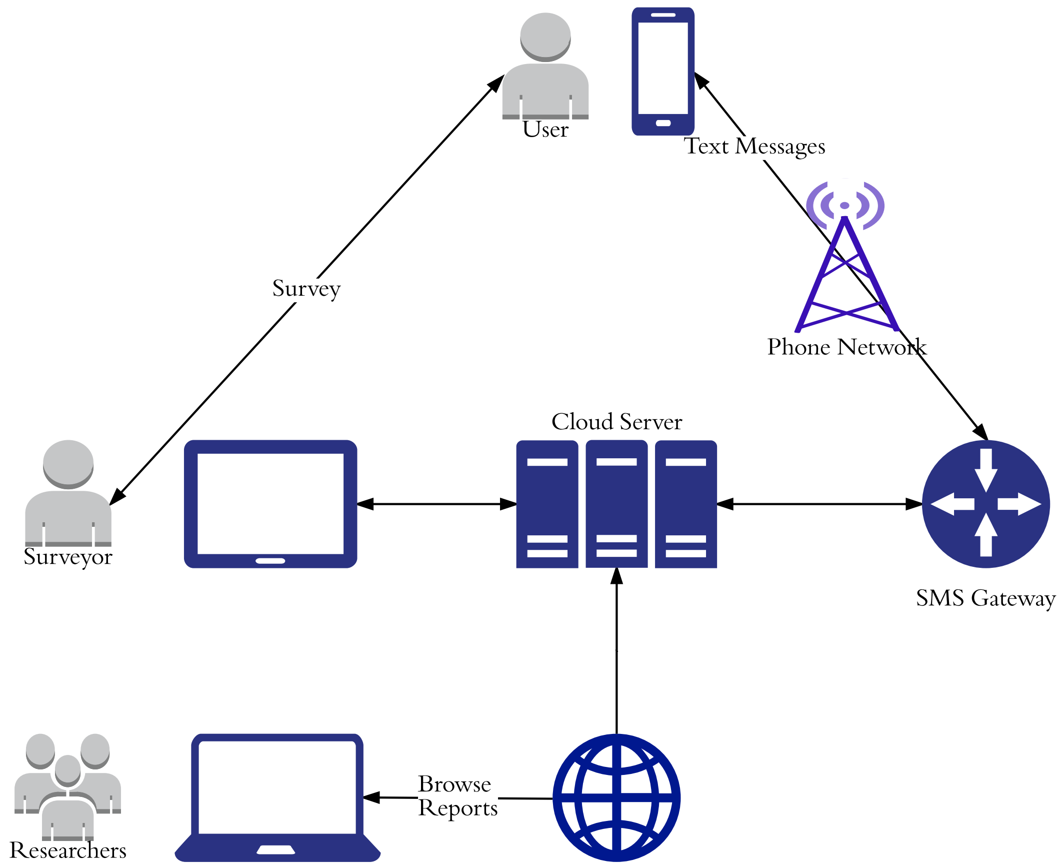

Figure 5.2: Text Message System Flow Diagram

Physical Activity

For the physical activity system, the main server ran on Apache Tomcat. The server ran continuously with Java and Spring frameworks, which allowed it to schedule text message sending. In this study, text messaging was scheduled for 4 different times daily. At the appropriate time, the server collected user settings for each user and, depending on their preferences, selected one text or video message for each participant. Then it sent the list of text messages and the recipients to Clickatell. The Clickatell API took the user phone numbers and the text messages as input via an XML document, and sent the text messages to the participants.

5.2.3 Functionalities

In this subsection, we will discuss the differences of functionalities of our solution systems.

Smoking Cessation

In the smoking cessation system, the text messaging system had a number of functionalities. It collected information about the participants from the database. It created a set of participants everyday in the morning and sent them a good morning message, which also asked for the participants preferences for that day. If the participant did not reply by midday, the system selected a random text message from the pool. The pool for each person consisted of text messages that they created for themselves, their personal preference, their status in the study etc. The system recorded when a person was last sent a text message. The frequency of text messages differed between participants from different groups. After the initial text messages, there were timed text messages for each participant depending on when they received their last text message and the appropriate interval for their group and status. Depending on these values, text messages were created by the main server, and the text messaging gateway collected these messages after a short time interval. The gateway sent the collected outgoing messages and sent them to respective participants. The main server had a timer for each participant and when the timer went off, it selected a text message for the participant from the pool and put it in the outgoing message buffer. The sms gateway communicated with the buffer and collected the messages to send.

Physical Activity

In the physical activity system, the participants used their android application, which detected their amount of physical activities. It also had an e-Journal that kept track of their performance. The application had a text messaging settings option, which let the participant select from a number of options. The server waited for an alarm to trigger for each cycle of message sending. When the alarm was triggered, the server checked the settings for individual participants. It checked what type of messages the participant preferred and selected a random text/video message from that pool for that person. Then, the list of phone numbers and the text messages were sent to the text Clickatell messaging gateway and those messages were delivered to the users.

5.3 Evaluation

In this section, we will discuss the evaluation methods that we used for both the systems.

5.3.1 Smoking Cessation

In the Smoking Cessation study, the participants were asked about how helpful the text messaging system was to them during several of the survey visits. The question was asked for both the intense text messaging and minimal text messaging groups. Both groups reported that the system was very helpful to them. The question was asked a total of 442 times and less than 3% of them disagreed on the effectiveness. On the other hand, about 89% of the replies were that they agreed, somewhat agreed or strongly agreed about whether the text messaging was helpful for them. The pattern is similar among the minimal and

Table 5.1: Comparison between different intervention and motivational systems

Smoking Cessation	**Physical Activity for Cancer Survivors**
Daily morning messages	No morning messages
Participants choose their message type daily	Participants can choose message type from the app
Message time depends on their reply	Message time is same for everyone
Uses an Android device as text message gateway	Usage Clickatell as text message gateway
Outgoing messages limited for android outgoing limit	Outgoing load is handled by Clickatell
We only had text messages	Video message links as well

intense groups. The data is shown in Table 5.2.

From the database, we also note that more than 70000 good morning text messages were sent and 40% of them were replied. One reason for the low rate of reply might be that the participants received text messages regardless if they selected their preferred type for the day or not (Table 5.3).

The participants created 36 customized messages that were sent to them more than 1200 times in total. Additional to these, we also looked at the carbon monoxide level in exhaled breath of the participants throughout the study and and found that the level of carbon monoxide was decreasing in each visit (Table 5.4).

5.3.2 Physical Activity

For validation of the system, we looked into the weekly journal entries of the participants for this system. The study was a pilot one and there were only 5 participants who replied to questions regarding the effect of text messaging in their weekly journals. When they were asked about if they were inspired by the text messaging system, 4 of them replied positively. If a larger study is conducted with the same system, we can have a better idea about the effectiveness of the system.

5.4 Conclusion

In this chapter, we showed how different intervention systems can be implemented on a single structure and how various customizations of the system can be utilized. Both systems have some pros and cons, but to design similar intervention systems, we can follow these models and choose the necessary features to generate the new model.

Table 5.2: Feedback from Smoking Cessation Participants over different visits

Visit	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
3	1	4	1	18	11	90	45
4		1		8	3	37	19
5			1	4	5	40	19
6		2	1	3	5	32	22
7			1	1	1	12	7
9		1		1	3	8	10
10		1		1	3	9	3
11					1	5	3
Total	0	9	4	36	32	233	128
Percentage	0.00%	2.04%	0.90%	8.14%	7.24%	52.71%	28.96%

Table 5.3: Response for morning messages

Group	Morning Messages	Not Replied	Replied	Reply Percentage
Intense	39288	22684	16604	42.26%
Minimal	31001	19450	11551	37.26%
Total	70289	42134	28155	40.06%

Table 5.4: CO (Carbon Monoxide) Reading statistics in different visits

Visit	1	2	5	6	7	9	10	11
Time	Start	Start	Q-day	Q+7d	Q+2w	Q+6m	Q+12m	Q+18m
Max	77	60	61	36	36	31	13	19
Min	1	0	0	0	0	1	0	0
Average	14.08	13.83	10.95	7.69	7.09	6.88	4.78	5.25
StdDev	11.46	11.08	10.39	7.85	7.24	6.02	3.33	4.83

CHAPTER 6

SMOKING DEPENDENCY MOBILE SURVEY SYSTEM

6.1 Introduction

Smoking and tobacco related cancers are very common among Native Americans. Gathering information during different phases of smoking cessation can help us understand different factors that may work during smoking cessation. We present a survey system designed to collect data for several phases of smoking cessation. We designed and developed a survey system that helps researchers to collect data from people who were going through different phases of smoking cessation. We evaluate this system from the experiences of end users and by generating reports.

A person goes through several phases as they quit smoking. To understand the different factors for motivation, we needed to create extensive surveys to question those who are in the act of stopping smoking. A well-organized survey allowed us to collect enough data that showed us patterns in behavior, which eventually led us to the main objective, to understand the behavior of someone who hopes to stop smoking, and how to make smoking cessation programs more effective. The system we developed was used to study smoking dependence in the Native American population in the Northern Plains of South Dakota.

6.2 Motivation

There are several scenarios currently plaguing researchers that we were hoping to address in the creation of this survey software. They are as follows:

Scenario 1: A researcher wants to create a survey questionnaire for a controlled group. She/he wants the questionnaire to be available only to a particular group of participants.

Scenario 2: A researcher wants to have some trained personnel to help participants to take the survey. The participants may live in remote places. The trained personnel should be able to carry around the device that is used for the survey. The personnel want to submit survey responses remotely.

Scenario 3: A researcher wants to check the progress of a participant under the study via reports, graphs etc. She/he needs an interface for generating these reports.

To address these problems, we present our survey application system. Using this system, a researcher can create a questionnaire for the control group via website. The trained personnel can collect user data in their iPad using the survey application.

6.3 Required Features

We identified several characteristics and functionalities that may improve a general survey application system. The basic requirements of the system are outlined in this section.

6.3.1 Modularity

The survey system should be such that it can be divided into several independent components that can communicate between themselves. The necessity of independent components is to ensure the rest of the system is running, even if a part of it is not working. For example, even if the question generation component is not working at a given moment, the system should not stop users from receiving the existing surveys and submitting a response.

6.3.2 Questionnaire generation

A survey has a set of questions. The set of questions can be divided into several sections. An interface is required for this questionnaire generation. This interface should only be accessed by the administrator/researcher and should be simple enough for a person to generate surveys with many sections and many questions.

6.3.3 Parsing

If we want to design a dynamic survey application system, we must ensure that the questionnaire can change over time. So, it is not feasible to store survey questionnaires in local devices. There are choices of questionnaires that may vary from user to user over time. Therefore, the application should be able to parse complicated data types with several sections, each section containing several questions of different types, and possibly having single or multiple responses. To accommodate all these, its easy to see that an elaborate parser is needed at the client application end.

6.3.4 Dynamic application

As we understand from the previous discussion, the user end application should be very dynamic. It should be able to render different questionnaires. The application should show different types of questions with their responses correctly. The application should be able to change itself depending on the participants and their status.

6.3.5 Control of data

The most important part of a survey system is the survey response data. The data should be stored in such a way that the anonymity of the participants are ensured. On the other hand, the response data should be available to the researchers for further analysis. This data will be used to generate different reports. It should also be available to the researchers in a supportive format.

6.4 Our Approach

To solve the problem of creating a dynamic, modular survey system, we developed the survey system described here. The system consists of several components, and ensures correct flow of survey questionnaire generation, performing survey and report generation. In this section we discuss the functionalities and the architecture of our system, and how we developed and deployed the system.

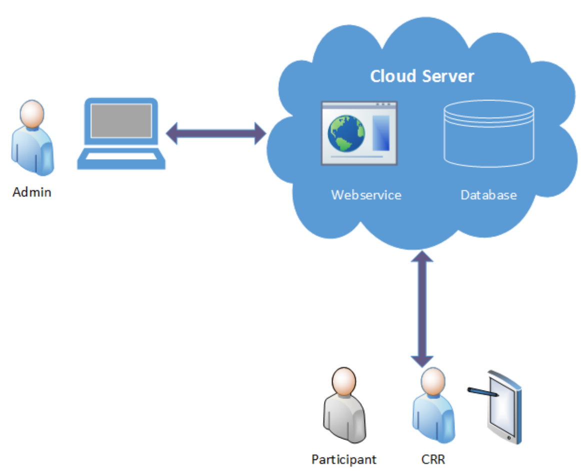

Figure 6.1: Data Flow Diagram

6.4.1 Functionalities

In our system, the admin created survey questions from the website, where there was an interface for creating these surveys. A survey, as mentioned, can have several sections each having several questions. The question types could be single answer, multiple choice or simple text. Only the admin had the privilege to add questions in surveys.

In our system, the survey was performed on an iPad application. End users (data collectors) used this application to collect data from the participants in the survey. The application communicated with the server and collected the questionnaire depending on the phase of quitting of the participant. The application stored the information collected from participant and saved it in the server.

6.4.2 Architecture

In the server component, the database was on the bottom layer. It was accessed only by the web services on top of it. The server had one layer that had several web services. These web services were used to communicate with the database. The web client was hosted in the cloud server and from it an admin added survey questionnaires, generated survey reports and monitored improvements among participants. The iPad application communicated with the web services to collect questionnaires and submit survey responses. All the clients used SOAP to communicate with the web services.

6.4.3 Development and deployment

The web interface was developed using C#, ASP.NET, HTML5 and CSS technologies. The web service interface was designed in C#. For the database structure, a relational database management system (RDBMS) was used (MS SQL Server 2012). A Windows Azure cloud server hosted the database, the web services and the website. The survey application was developed for iOS platform, and iPad devices were used to run the application in testing and production.

6.5 Evaluation

In this section, we will discuss the evaluation of our solution based on the required features.

6.5.1 Modularity

The system we designed has some basic components. There was a website for generating different survey questionnaires and reports. The iPad application was in the client end and allowed a medical professional to administer the survey and submit the responses. Other components were the web service interface and the database. These independent components communicated among themselves.

6.5.2 Questionnaire generation

By using the website, the researcher (working as an admin) created survey questionnaires. Any number of surveys could be created, each having several sections and many questions. The question creation page was very intuitive and easy to use. The survey questionnaires could be modified, updated and deleted from this interface.

6.5.3 Parsing

The survey application on the iPad could communicate with the database by using web services. It could ask for a specific survey according to the participant and their status. After getting the set of questions, the application parsed this into a data type for its understanding so that it would be shown later to the user correctly. We had an elaborate parser that helps us to parse complex XML files consisting of the questionnaire.

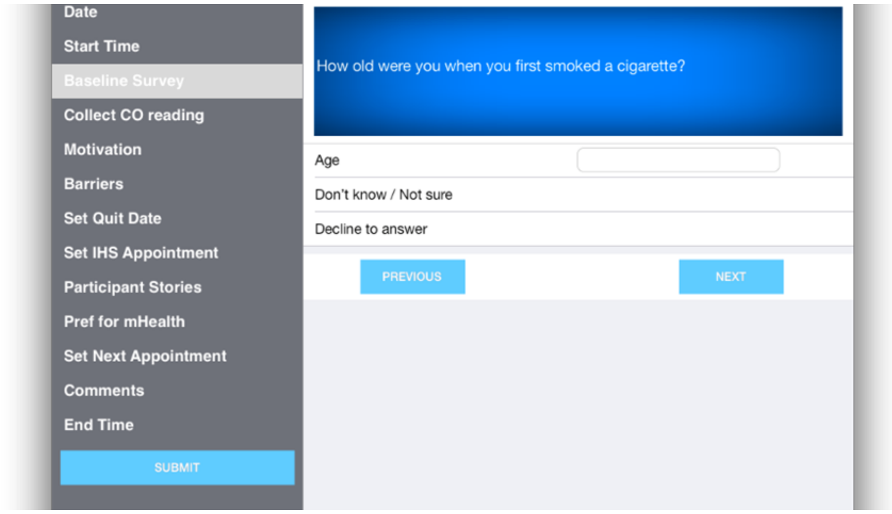

Figure 6.2: Question with multiple types of answers

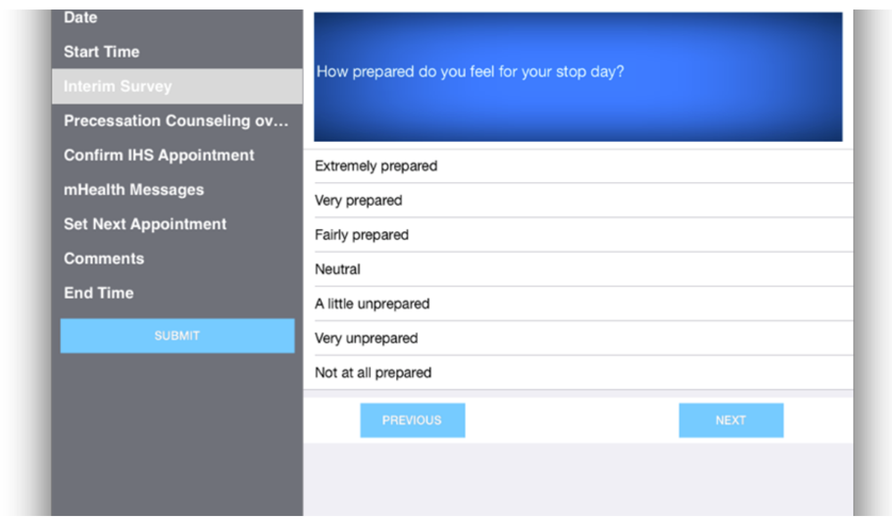

Figure 6.3: Questions from a different visit

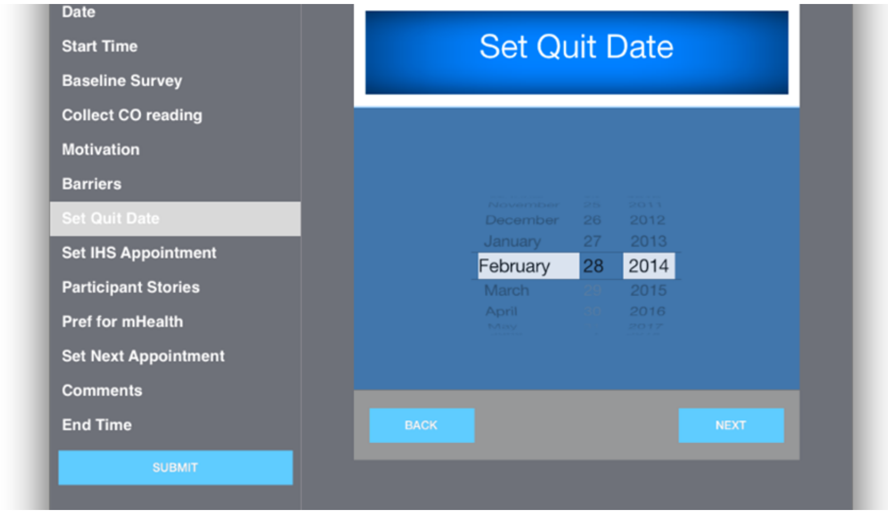

Figure 6.4: Question with Date/Time as input

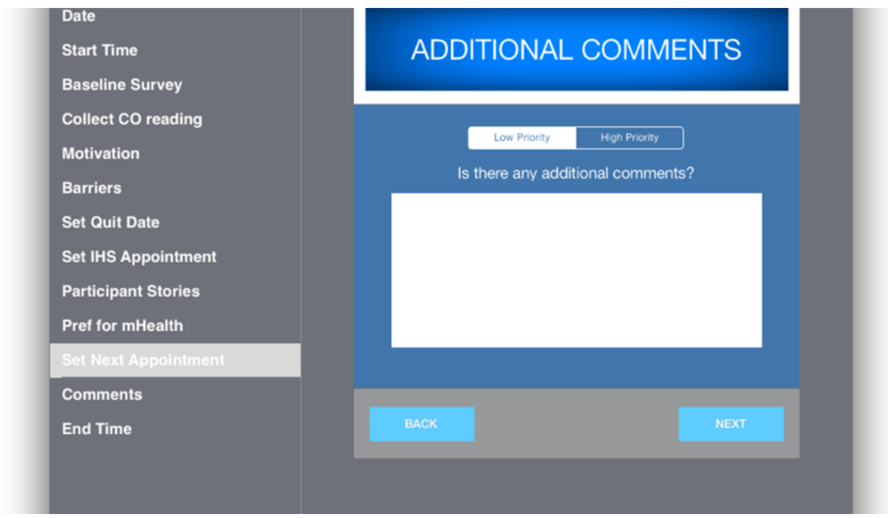

Figure 6.5: Question for additional comments

6.5.4 Dynamic application

The application we developed was very dynamic. In the Smoking Cessation project, there were 15 groups and each person has to go through 11 visits of surveys. Our application could fetch the questionnaire for that survey and change itself accordingly. Dynamic pages helped the applications to work for a variety of types of questions.

6.5.5 Control of data

In our system we used a HIPAA compliant server. We ensured in our system that the participants' identities and anonymity were protected. As we set up our own database, it was much easier for us to generate the reports and show them in the website. Even if there was a new change in the database, the change was implemented on the client side as well. The updates of the application were usually very swift.

6.6 Conclusion

Smoking related health hazards are life threatening and it is important that a proper study is conducted to understand the status and motivating factors of people who are going through smoking cessation. For all these, we needed a survey tool that helped us in generating questions, conducting surveys, and generating reports.

CHAPTER 7

MHEALTH SYSTEM FOR PAIN LEVEL DETECTION

Pain is a prevalent symptom in many different diseases and medical conditions. A lot of illnesses show different levels of pain symptoms. Sometimes the level of pain is a measure that indicates the severity of a patients condition. One such scenario is in the case of palliative care. It is essential to detect the pain level for cancer patients, who require priority health service. In this chapter, we discuss our design and implementation of an mHealth system to detect pain level from the images of faces taken by a smartphone camera.

7.1 Research Challenges

The primary research challenge in identifying pain levels was to come up with appropriate features from the data. Other challenges included data collection and storage, anonymization of data, extract features from data and using data mining and machine learning techniques to detect the pain level. In brief, we can say that we needed to generate a training data set, train our system with this training data and evaluate the system by testing it on some test data set.

7.2 Related Work

Bruera et al. [16] described a simple method for regular assessment of symptom distress. They had eight analog scales from 0 to 100 mm for various symptoms. This method was called The Edmonton Symptom Assessment System (ESAS) and was very useful in the palliative care setting.

Daut et al. [25] developed Wisconsin Brief Pain Questionnaire (BPQ). This was a self-report instrument used to assess pain in cancer and other diseases. Patients used a scale of 0 to 4 to assess their current pain, usual pain, and worst pain. They concluded that the method was adequately reliable and usable in research.

Cleeland et al. [20] described the development and application of Brief Pain Inventory (BPI), which measured pain in sensory and reactive dimension. It used a scale of 0 to 10 for pain intensities. It collected maximum pain, minimum pain, average pain and current pain. They described the measurement system to be simple and useful in multiple cultures.

Ahmad et al. [4] evaluated different face detection and recognition methods. They analyzed different learning methods and discussed their accuracy on different datasets.

Nanni et al. [62] discussed several variants of Local Binary Pattern (LBP) for image analysis. In that study, they used a database of neonatal facial images for classifying pain. They concluded that elongated quinary patterns (EQP) performed better than other methods.

Monwar et al. proposed a video analysis technique to classify painful and painless faces [60]. They implemented an automatic face detection and feature extraction method. Then they used an artificial neural network with standard error back propagation algorithm to classify.

Kaltwang et al. proposed a fully automatic approach for pain detection using facial images [46]. Their approach has three steps: feature extraction, pain estimation, and fusion. For feature extraction, they combined Local Binary Patterns, Discrete Cosine Transform, and facial landmarks. For continuous intensity estimation, they used Relevance Vector Regression. They showed that using the fusion method, the accuracy of the estimation was increased.

7.3 Our Approach

In this section, we will discuss the different phases of the system, the methods used in collecting the data and different data analysis techniques.

7.3.1 Phases

In our efforts to find a solution for detecting pain level, we modeled our solution to train the system in phases. There were longitudinal and cross-sectional studies performed for the data collection. The longitudinal study data was collected from six women with advanced breast cancer over three months. In the cross-sectional study, data were collected for each for exactly one time. One time images from Bangladeshi, Nepalese and North American patients with advanced cancer were collected. Combining the two sets of data was the basis of the predictor algorithm that we designed.

7.3.2 Data Collection

The collected data included the Amader Gram Survey and a facial photo of the participant with the help of a mobile phone camera. From the survey, we collected the current pain level and the average, highest and lowest pain levels in last 24 hours. There were also other symptoms as drowsiness, nausea, sleep quality, sleep quantity, depression, etc. For all these features, a scale of 0 to 10 was used. For example, no pain was assigned 0, and extreme pain was assigned 10. The data was stored in the database with anonymization. From both the studies, data was collected similarly. Images were captured before the survey questions were answered.

7.3.3 Data Analysis

For the analysis of the symptom data, we use several regression and classification methods. We look at the correlation coefficients within different symptom values and noticed how they are interrelated.

For analysis of the image data, we use eigenfaces. To generate the eigenfaces, we needed a set of training data. We collected the training data from the set of longitudinal and cross-sectional study data. We also included the symptom variables as extra feature variables. Using them, we trained our system. After training, we tested the system with individual entries. This model in Figure 7.1 describes the flow of our system.

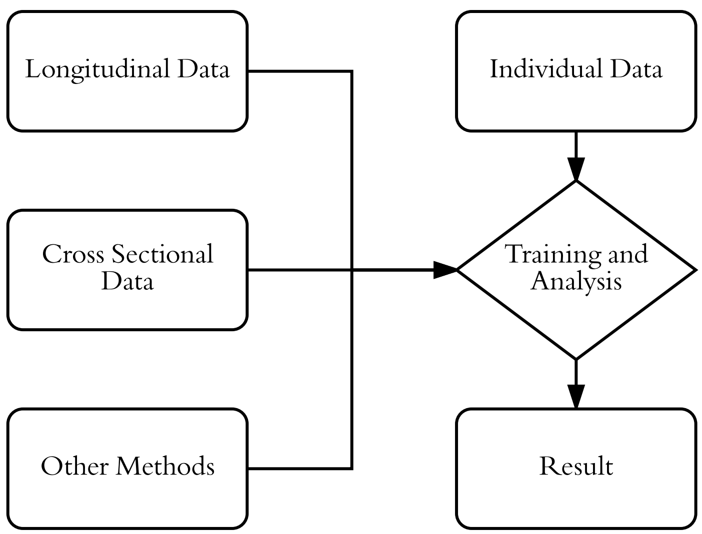

Figure 7.1: Training and Analysis of Image Data

7.4 Evaluation

We had 408 images from 6 participants in the longitudinal study. We also had about 1043 entries in the cross-sectional study from participants from

Bangladesh, Nepal and South Dakota. Table 7.1 shows the distribution of longitudinal pain level.

Table 7.1: Pain Level Distribution in Longitudinal Data

Pain Level	Percentage
0	5.05%
1	3.19%
2	6.71%
3	17.66%
4	20.19%
5	13.81%
6	11.02%
7	8.83%
8	2.86%
9	2.52%
10	8.17%

In our initial analysis, we wanted to create a predictor for pain from the symptom variables. Using symptom variable as inputs and pain values as output, we trained a system. The training and the testing was performed by the tool Matlab. We used different algorithms as the simple tree, complex tree, linear SVM, quadratic SVM, kNN, etc. to check the accuracy of the predictor. We noticed that there was a high correlation with the pain value with other features in the Bangladeshi population. This is one of our findings from this study. This relation is showed in Table 7.2.

We also did some image analysis from our collected data. For image analysis, we used two methods. First, we took the longitudinal data as training set and cross-sectional data as the test set. Later, we took part of cross-sectional data as training set and we tested on the rest of the data.

We took facial images and assigned them with specified pain level, and trained the system using eigenfaces. Afterwards, we used the test set to check the accuracy of the system. For the longitudinal test set, the average error was 1.58. For the cross-sectional test case, the average error was a little higher, 2.6.

7.5 Conclusion

Though our analysis does not show very low error, our study is unique in many ways. We have collected a big data set, which includes cross-sectional and longitudinal data. It was obtained from different locations around the world. Using this dataset will be a base for our future goal, which is to develop an individualized pain tool, which will be trained by both a person's data and data from the population. This will enable us to improve the accuracy of the personalized system.

Table 7.2: Analysis of Amader Gram Parameters in Cross-sectional Data

Predicting Pain level	Simple Tree	Complex Tree	Linear SVM	Q-SVM	Coarse KNN	W-KNN	Boosted Tree
Total	70.7	68.9	72	72.2	71.8	72.9	71.5
Bangladesh	84.1	82.2	84.8	82.3	80.8	83.8	80.8
Nepal	50.9	45	56.8	53.5	52.5	53.2	52.3
South Dakota, USA	55	49.6	56.1	55.6	54.3	54.3	54.5

CHAPTER 8

HEALTH MANAGEMENT TECHNOLOGY FOR MARGINALIZED POPULATION

8.1 Introduction

Latest innovations in computer science help the scientists and engineers to develop high-end devices with increased computational power and speed. Modern trends in computer science and healthcare focuses on gadgets and complex computation where the users are from financially better situations. In many cases, the solutions tend to be costly. Healthcare should be the right of every person regardless of their economic capabilities and that is why it is necessary to work on system solutions, which aim to give healthcare to people at a low cost.

In my research, I worked for health solutions for people who are from a marginalized population of the system. In this chapter, we will discuss what we learned about developing mHealth system for these people and what the impacts are that we have from our work.

8.2 Background

In previous chapters, we have discussed how we developed different mHealth solution systems. We mostly described the development and deployment of the systems and discussed the direct contribution of those studies. In this chapter we want to focus on some long term contributions of these systems. We can use the smoking cessation by mHealth intervention as a case study and explore the findings and contributions.

In the smoking cessation study, we wanted to develop an intervention system to motivate participants to quit smoking. The study was focused on the

Native American population of the Northern Plains. This population suffers from tobacco and smoking related cancers at higher rate than others. Due to cancer recurrence and lack of healthy life practices, the rate of fatal occurrences due to smoking and tobacco related cancers are also very high.

One significant feature of this population is that people of this population live in a place which is technologically behind from the rest of the country. There are issues regarding connectivity due to lack of infrastructure. Many people in the area have trouble finding constant telephone services, let alone high speed internet. People from lower socio-economic conditions are not able to use high-end mobile devices.

To solve this problem, we need to delve into the current practices and explore different ideas. We will discuss how we collaborated with different teams to find our solution. Before discussing those, we present some related works and state of the art technologies that has been used.

8.3 Related Works

The study of smoking cessation has gone on for a long time. Different behavioral and medical approaches has been in practice to help those quitting smoking. There are nicotine replacement therapies, where the smokers are given nicotine with gums, sprays, patches and lozenges [78][81]. These alternative nicotine inputs do not have any harmful carcinogens like smoking and tobacco. Researchers also use motivational counseling and interviews to help quit smoking [14] [45].

There is a current trend of utilizing technology in smoking cessation. Different types of smart e-cigarettes [74], smart-lighter [6], breathalyzer [3] are used to collect rate of smoking and carbon monoxide levels.

Social Media is another tool used as cessation mechanism. There are Facebook communities where members are motivated to stop smoking. People following these community pages and Twitter profiles can gather information about strategy and motivation to quit smoking [82][68]. Study shows that the potential of communication in social media are not utilized in these systems [32].

There are also some popular application on androids and iPhones. Abroms et al. did a study on the effectiveness of those apps and described that they were hardly following the guidelines and there are a lot to improve to make them effective [1][2].

Another widely used method for smoking cessation is text messaging. This is a globally affordable intervention method [71] [39]. Participants receive regular text messaging which motivates them to stop smoking. We built our system on the same idea.

We analyzed the related works and propose the taxonomy in Figure 8.1.

8.4 Our Approach

In this section we will discuss our approach of finding a solution. First, we will talk about forming the team. Then we talk about designing and development of the system. Finally we discuss how the system was deployed and was used by the participants.

8.4.1 Interdisciplinary works

Our study team consists of people from different backgrounds. We had medical doctors specialized in oncology, researchers who work with Native American cancer patients, statisticians and a software development team. Having a multidisciplinary team was very useful because everyone in the team brought something important from their background. The doctors helped with

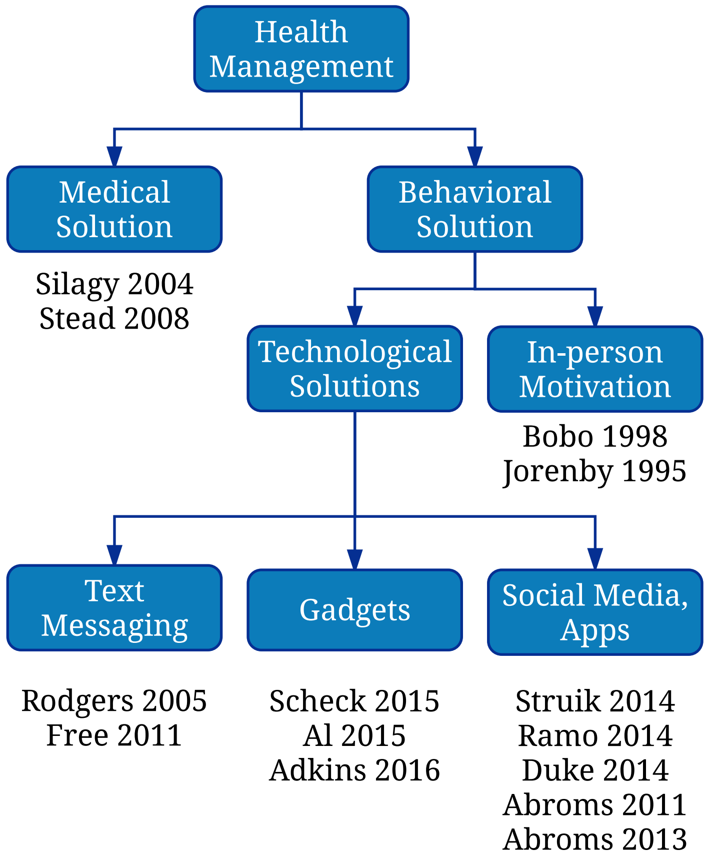

Figure 8.1: Taxonomy of Health Management Systems

recognizing important factors related to smoking and cancer, the research team provided insights on the Native American population, the development team combined the ideas and the statisticians analyzed the data.

8.4.2 Design of the system

In our study, we wanted to collect data from Native American smokers who want to quit. They were part of an eighteen month long study and during this time we collected data from them. They were also part of the intervention system that we developed. To design the data collection tool (described in Chapter 6) and to develop the smoking intervention system using mHealth (described in Chapter 3), we had regular meetings between the members of the team. We discussed what data are we trying to collect, who will be collecting data from the participants, how often the data should be collected, what should be the interface of the data collection tool, what kind of text messages will be sent, how often the messages will be sent, what are the factors for choosing a specific message, what kind of customization is needed etc. These detailed meeting helped us figure out what should be the design of the system.

8.4.3 Development

We developed the data collection tool to collect periodic data from the participants. The data collection tool was designed in a way, so that the surveyors were able to browse through the participants easily and could submit their answers to the questions in each visit. For this development, we implemented an agile process. We had the initial build of the system and communicated directly with the whole study team and the surveyors. This helped us improve the iPad application and after a few iterations, the application was completed and ready to be used. For the text messaging system, we also went through similar iterations.

8.4.4 Deployment and Functionalities

The iPad survey application was used by the community research representatives to enroll participants. The participants also went through a baseline survey. After that, there were periodic surveys. During visit 2, the participants were enrolled for mHealth text messaging intervention. They started receiving text messages daily for several times. There were daily morning messages, which the participant replied to update their preferable message type. There were in total 11 visits, and it took about eighteen months for the participants to finish their enrollment. During this time, they received regular text messages. A breathalyzer test was used to determine carbon monoxide levels in the exhaled breath of the participant during the visit. They also rated their satisfaction with the text messaging system during their survey visits.

8.5 Evaluation

Developing the system is just the first step towards finding an appropriate solution. It is also necessary to evaluate our system using different measures. We will discuss the effectiveness of our solution by the following features:

1. Contribution to applied science
2. Contribution to society
3. Multidisciplinary learning

We will discuss them in brief here.

8.5.1 Contribution to applied science

Motivational text messages are already being used in text messaging. The way our solution improved this, is by using customization for individuals. From our collected data, we see that people from this study was very positive about the text messages in their review. This was the first step of user evaluation of the system. The participants said that they found the text messaging helpful. On the other hand, the study team also collected carbon monoxide level in the exhaled breath during each survey visits. This physiological data is a clear sign of smoking and tobacco usage. We see from this data that the level of carbon monoxide is decreasing over time. That is also another indication of improvement. This indicates how a health management system can utilize already developed technology to give a better output.

8.5.2 Contribution to society

Our solution did not focus on costly gadgets. What we intended to do is to have a cost-effective solutions which can help people from marginalized demographics. We developed our system in a platform, which enabled people with very cheap phones to have access to the motivational messages. These messages were customized to the individual's preferences. They were also culturally sensitive and incorporated their life views, which targeted a specific population. This model can be used in other systems and other demographics as well. For the availability and the universally usable design, the system can be labelled as a technology for the betterment of service of man.

8.5.3 Multidisciplinary learning

This study accommodated members from different backgrounds to collaborate and learn from each other. This study will be a model for future studies where we would need similar expertizes from diverse scientific backgrounds.

8.6 Conclusion

In this chapter, we have discussed how we used our system to maintain healthcare and evaluated it with actual physical parameters. This shows the strength of our system design and we can utilize this model in other projects. In Chapter 7, we discussed how we can use our system to detect pain levels from smartphone camera images. Our findings shows us that a similar model could be used for detecting other physiological parameters.

Around the world, we notice that there are chronic diseases like hypertension, diabetes and asthma and these diseases require regular maintenances from the patients. We can use our system architecture and designed model for these diseases where we utilize some collected benchmark data and combine this with an affordable solution for people and improve the life of common people.

CHAPTER 9

CONCLUSION

9.1 Summary

In this dissertation, we have discussed how we designed and developed our motivational and intervention systems with mHealth tools. We have also considered how we can use these tools to monitor patients for their health parameters and how can we develop algorithms and models for this. We have developed a culturally tailored and customized text messaging system to motivate people to stop smoking. We also have developed a motivational system, which includes a text and video messaging system and e-Journal, to motivate cancer survivors to be more physically active. We have developed a data collection tool for participants of an intervention system. We also developed a model and analyzed cancer patients facial images to detect their health condition.

9.2 Contributions

In this section, we will discuss the contribution of our mathematical model development, the design of our system and usability of the different systems to be used for diagnosis and health-care maintenance.

9.2.1 mHealth Intervention for Smoking Cessation

Tobacco and smoking-related cancer are prevalent among Native American people in the Northern Plains. We designed and developed a customized and culturally tailored text messaging system, which sends motivational text messages to participants. The quantity and types of the text messages are different for different groups of people. As the participants chose daily the types of messages they want, we have gathered a lot of data from their responses and also their attachment to the system. For this system, we used an Android phone as text messaging gateway. We evaluated the system and showed the effectiveness of the system from user feedback and carbon monoxide reading of the participants during different visits.

9.2.2 mHealth Motivation for Physical Activity

We also developed a similar system for cancer survivors to motivate them for physical activity. Cancer survivors have a higher rate of cancer recurrence. To maintain good health, it is essential that they have a healthy life with healthy food and regular physical exercise. For our system, we developed a text message system which sends the participants motivational messages. We also developed an Android app, which the participants use as e-Journal, to post regular updates about their physical activities. We collected pilot data and evaluated the system by user feedback and application efficacy.

9.2.3 Smoking Dependency Mobile Survey System

For the Smoking Cessation study, we required a tool for collecting participant information from baseline and periodic surveys. To integrate it into our solution, we designed and developed the survey systems. We developed an iPad application to collect data from participants. The application was dynamically designed. It was used to collect data from 256 participants, in 15 groups and 11 visits. We also evaluated the system in this dissertation.

9.2.4 Pain Level Detection

In this dissertation thesis, we also propose a system for pain level detection using smartphone camera images and symptom values. Through Amader Gram symptom survey we have collected pain values, related symptoms and images of participants in our study. We analyzed data from two major studies: Longitudinal and Cross-sectional studies. We have collected more than 1100 sets of cross-sectional data and about 500 sets of longitudinal data. Our research gives direction for the development of a future a personalized pain tool.

9.3 Intellectual Merit

This dissertation thesis includes our contribution in design and development of the systems, mathematical model, and the algorithms. We have also published on most of the topics and plan to continue this work and publish future papers.

9.4 Broader Impact

In this section, we will discuss the short-term and long-term impacts of our studies.

9.4.1 Short-Term Impact

Our systems were used by participants in underdeveloped areas, and our mHealth system helped the participants to quit smoking and be more physically active. These studies have had direct positive outcomes on the participants which has improved their health condition. Our pain detection study will help future researchers with the data and our results.

9.4.2 Long-Term Impact

The systems discussed here will help people in several ways. First, we have tried to design low-cost solutions for non-invasive diagnosis methods. We have also designed systems that use multiple components to ensure faster healthcare. We have also presented a standard of development mHealth system, where many components communicate with each other. And finally we hope to achieve a better quality of life for the patients through our small steps towards the excellence of the system.

9.5 Future Works

From developing our mHealth systems, we have also designed the basic framework of similar systems. This structure and the methodologies can be used further in future developments of similar systems. Our analysis shows pros and cons of using development tools and methods for similar systems. It will be a guideline for other intervention and motivational systems.

For pain level detection, we believe there are still areas where the methods can be improved and thus give us better results. Our research also starts the path for the development of a pain tool that can be used for individual training and detection.

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