7-1-2013

Toward an mHealth Intervention for Smoking Cessation

Golam Mushih Tanimul Ahsan
Marquette University, golammushihtanimul.ahsan@marquette.edu

Ivor D. Addo
Marquette University, ivor.addo@marquette.edu

Sheikh Iqbal Ahamed
Marquette University, sheikh.ahamed@marquette.edu

Daniel Petereit
Rapid City Regional Hospital

Shalini Kanekar
Rapid City Regional Hospital

See next page for additional authors

Accepted version. *2013 IEEE 37th Annual Computer Software and Applications Conference Workshops (COMPSACW)*, (July 2013): 345-350. DOI.

Authors
Golam Mushih Tanimul Ahsan, Ivor D. Addo, Sheikh Iqbal Ahamed, Daniel Petereit, Shalini Kanekar, Linda Burhansstipanov, and Linda U. Krebs

Toward an mHealth Intervention for Smoking Cessation

G. M. Tanimul Ahsan, Ivor D. Addo, [...], and Linda U. Krebs

Abstract

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 usage. In this paper, 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 proposed solution implements machine learning algorithms that take the participant's demographic profile and previous smoking behavior into account. We discuss our preliminary evaluation of the system against a couple of pseudo-scenarios and our observation of the system's performance.

Index Terms: Theory of Planned Behavior, Phase-based Framework, Smoking cessation, mHealth

I. Introduction

Smoking cigarettes, pipes and cigars leads to several types of health-related problems including lung cancer and heart diseases [1]. According to the US Center for Disease Control and Prevention (CDC) [1], smoke-related health issues accounts 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 others 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 work-in-progress solution logs the demographic information of the smoking cessation program participants in addition to their self-annotated smoking behavior. We propose 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 that the targeted user belongs to.

We discuss the motivation for this study in section II and highlight a number of related works in section III. We then describe the characteristics of the system and implementation details in section IV and V respectively. Our evaluation, approach and findings are described in section VI and VII correspondingly.

II. MOTIVATION

With tobacco dependence noted as the leading preventable cause of death in the US [11], we seek to use our proposed intervention strategy to drive down tobacco use in communities that have a high smoking prevalence rate. The production-ready solution will be 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 [4]. Notably, smoking prevalence among Native Americans in the Northern Plains of South Dakota is approximately 44.2% [6]. Smoke-related health problems account for about 443,000 deaths or 20% of all deaths recorded annually in the US [4]. 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 future application of this intervention strategy aims 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 for Planned Behavior, develop and adapt existing tobacco cessation interventions for use with adult Northern Plains

American Indians who smoke cigarettes daily.

The outcome data will also reveal 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 will be identified. We expect our study results to significantly impact tobacco use among Northern Plains American Indians while providing insight into effective cessation interventions for this population.

III. RELATED WORK

Baker et al. [3] 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. [2] proposed some recommendations and guidelines for curbing smoking dependence in healthcare. In that article, there are a number of 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 [4] 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 be ready to quit within a certain period of time, more than 50% of them were open to going through a motivational phase that might lead to an intervention.

Free et al. [6] 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. [5] evaluated mobile phone-based interventions for smoking cessation and concluded that using a mobile phone for intervention increases the probability of a long-term smoking cessation. They analyzed five different methods which studied the effect of using a mobile phone for smoking cessation in order to arrive at that conclusion. This proves to be an improvement on their previous findings which suggested that there is no long-term effect of using mobile phone on smoking cessation. We believe our proposed approach will prove to be more effective for long term behavior change toward cessation.

Ajzen [7] 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. cause 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 the he or she wants to behave, what the surrounding expects of him or her, how motivated he or she is about that specific behavior and what behavioral controls and ability he has. The author also provided a mathematical model about how these components relate to each other.

Norman et al. [8] 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. Yet 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.

IV. SYSTEM CHARACTERISTICS

Some of the key components of our intervention approach include:

A. 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 are furnished with low-cost mobile phones. Each mobile device is equipped with text messaging capabilities. The SMS feature is the most widely used mobile data service today [12]. 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 can afford to use.

B. Machine Learning Recommender Algorithms

Our solutions seeks to deliver personalized and evidence-based motivational SMS messages to the program participants through the implementation of machine learning algorithms that take the participant's demographic profile and previous user behavior into account. A *user-based* recommender engine algorithm is 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.

C. mHealth

Mobile Health (mHealth) represents the advancing subclass of digital health solutions that apply mobile phone technologies in the healthcare industry. More than three billion people worldwide use mobile devices [12]. With the emergent 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 form factors 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.

D. Theory of Planned Behavior

Social science theories have evolved to better predict how attitudes lead to new behaviors by integrating models and including additional determinants of behavior such as intentions and social norms. The Theory of Planned Behavior (TPB) offers a mathematical model for the behavior of a person. A participant's actual behavior depends on several factors. The major factors include behavioral beliefs, attitude towards behavior, subjective norms, normative beliefs, controlled beliefs, perceived action and intentions [7]. According to the theory, all these factors modify the actual behavior. The Theory of Planned Behavior attempts to map human behavior to these different properties and factors. Subsequently, TPB describes how a person's behavior has changed over time.

E. Phase-Based Framework

A phase-based framework is proposed for the target study to help understand various behavior patterns during various phases of the intervention. We believe that 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 will be identified through the fusion of the aforementioned framework and theory. A better understanding of how interventions influence behavior at each phase will ultimately aid the development of an optimal smoking cessation program.

Participants in the cessation program will be evaluated during several phases. The first couple of phases are focused on *motivating* the participant to quit smoking. This phase can have an infinite length. If a participant becomes motivated, he or she will proceed to a *pre-cessation* phase. During precessation, the participant will identify a future date for quitting. The *cessation* phase commences when the participant is ready to deliver on the promised target date. After the cessation phase is complete, the participant will go through the *maintenance* phase. During the cessation phase, the participant might need medical help including access to nicotine patches etcetera. The phase-based framework ensures that the different stages of the cessation process are well understood and adequate preventive and supportive measures are taken according to the needs of the phase in question.

V. 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.

A. Functional and Non-Functional Features

The system generates motivational text messages and sends these automated text messages to participants. The system can also have a conversational two-way communication with participants by interpreting certain pre-programmed keywords including: "slip", "crave", "signup", etcetera. The solution makes use of a secure web site and web services to register users and display insights into the user's progress in the program.

The system also provides support for administrators to build surveys dynamically through a web administration portal. These surveys are used as evaluation vehicles for testing the efficacy of the smoking cessation intervention by constructing an engine that is used for building and administering surveys across multiple mobile platforms including Windows 8, and iOS. Our dynamic survey engine affords 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 is successively fed into a Health Insurance Portability and Accountability Act (HIPAA)-compliant cloud-based data store and, in turn, helps to improve the efficacy of the evidence-based algorithms used in the mHealth SMS intervention. The surveys collect demographic information regarding participants who are looking to eliminate their dependence on tobacco. Demographic information includes education, employment, gender, age, and more. The system also collects intent of enrollment which may include the amount of daily tobacco use, a target plan for quitting, and more. The system stores all the recorded information in a secure database system so that the end users' anonymity is protected.

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

B. Solution Architecture

As illustrated in Figure 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* which 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.

Fig. 2
Logical View of the Solution Architecture

C. 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 [2]. Table I illustrates some of the tailored messages stored in the database. Subsequently, the *recommender engine* is used to select the best-fit message to be sent to the participant as a response.

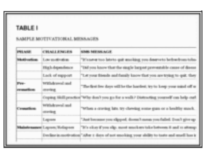

TABLE I

SAMPLE MOTIVATIONAL MESSAGES

PHASE	CHALLENGES	SMS MESSAGE
Motivation	Low motivation	[illegible]
	High dependence	[illegible]
	Lack of support	[illegible]
Pre-cessation	Withdrawal and craving	[illegible]
	Coping Skill practice	[illegible]
Cessation	Withdrawal and craving	[illegible]
	Lapses	[illegible]
Maintenance	Lapses/Relapses	[illegible]
	Decline in motivation	[illegible]

TABLE I
SAMPLE MOTIVATIONAL MESSAGES

D. Development and Deployment

For the SMS Gateway component, we built a Python script that runs on an Android device and interacts with our cloud service API. 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 iPads and Windows 8 Surface tablets. Apache Mahout is leveraged for building a scalable recommender engine.

VI. EVALUATION

To evaluate our mHealth SMS intervention approach, we plan on conducting the following tests:

- Evaluate the usability of the various solutions
- Evaluate Efficacy of the Intervention Approach

- Evaluate Performance of Recommender Algorithms

A. Usability of the System

We are in the process of performing an exhaustive usability study of the various solutions at play in our intervention approach. In the interim, 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. We hope to share the full-blown results of our study when the solution is implemented in the target communities.

B. Efficacy of the mHealth Intervention Approach

To evaluate the efficacy of the mHealth intervention approach, we will conduct 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 will be self-identified and self-referred after hearing or reading promotions disseminated throughout the target reservations. Participants who cannot afford cellphones will be furnished with mobile devices. The study is expected to last 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. The production-ready solution will target about 256 participants.

In addition, this study will employ 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 will be determined to test our hypothesis around the superiority of the mHealth approach.

Participants will be required to self-report their progress in the cessation program on a daily basis. The self-reported user behavior information will be logged and utilized for continually improving the SMS message recommender engine. Even so, the data logs will be mined to gain insight into the effectiveness of the mHealth approach in engendering behavior change. A cross-section of participants who engage in the mHealth intervention will be presented with evidence-inspired personalized messages while the other group will be presented with random messages. We intend to use 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.

C. Performance of Recommender Algorithms

To test the performance of our recommender engine algorithm, we built a number of scenarios and simulated the enrollment of 25 participants in our system with an equal opportunity to receive SMS messages from a list of 100 different motivational messages. We then evaluated the following popular *user-based recommender algorithms* against the corpus:

- Pearson Correlation Similarity
- Euclidean Distance Similarity
- Log Likelihood Similarity

Though, our sample size was significantly less than the expected production data set, we found the Euclidean Distance algorithm to be slightly faster than the other algorithms. We plan to execute this test again when we have production-level data to determine which algorithm produces the best results and also performs faster for our domain corpus.

VII. CONCLUSIONS

Our preliminary findings suggest that there are opportunities to deliver a personalized mobile health 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. All the same, we hope to conduct an exhaustive evaluation exercise in the near future and share our insights into the efficacy of the mHealth intervention approach in comparison with other smoking cessation strategies.

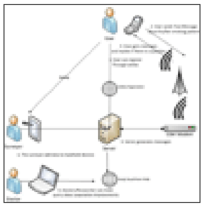

Fig. 1
Data Flow Diagram

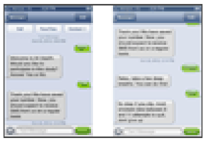

Fig. 3
Automated Messages for User Enrollment

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 is partially funded by the National Institution for Health (NIH) and will be used for a study of smoking dependence in Native American communities in the Northern Plains of South Dakota, US.

Contributor Information

G. M. Tanimul Ahsan, Marquette University, Milwaukee, Wisconsin, USA.

Ivor D. Addo, Marquette University, Milwaukee, Wisconsin, USA.

S. Iqbal Ahamed, Marquette University, Milwaukee, Wisconsin, USA.

Daniel Petereit, Rapid City Regional Hospital, Rapid City, SD, USA.

Shalini Kanekar, Rapid City Regional Hospital, Rapid City, SD, USA.

Linda Burhansstipanov, Native American Cancer Initiatives.

Linda U. Krebs, Native American Cancer Initiatives.

Article information

Proc COMPSAC. Author manuscript; available in PMC 2013 Oct 28.

Published in final edited form as:

Proc COMPSAC. 2013 : 10.1109/COMPSACW.2013.61.

doi: 10.1109/COMPSACW.2013.61

PMCID: PMC3809119

NIHMSID: NIHMS490486

G. M. Tanimul Ahsan, Ivor D. Addo, S. Iqbal Ahamed, Daniel Petereit, Shalini Kanekar, Linda Burhansstipanov, and Linda U. Krebs

G. M. Tanimul Ahsan, Marquette University, Milwaukee, Wisconsin, USA;

Contributor Information.

G. M. Tanimul Ahsan: golammushihtanimul.ahsan@marquette.edu; Ivor D. Addo: ivor.addo@marquette.edu; S. Iqbal Ahamed: sheikh.ahamed@marquette.edu; Daniel Petereit: dpetereit@regionalhealth.com; Shalini Kanekar: skanekar@regionalhealth.com; Linda Burhansstipanov: linda.krebs@ucdenver.edu; Linda U. Krebs: lindab@natamcancer.net

References

1. CDC. Tobacco-Related Mortality. [Retrieved on March 11, 2013];Center for Disease Control and Prevention. from: http://www.cdc.gov/tobacco/data_statistics/fact_sheets/health_effects/tobacco_related_mortality/

2. Raw M, McNeill A, West R. Smoking Cessation: Evidence Based Recommendations for the Healthcare System. BMJ (British Medical Journal) 1999 Feb;318:182–185. [PMC free article] [PubMed]

3. Baker TB, Mermelstein R, Collins LM, Piper ME, Jorenby DE, Smith SS, Christiansen BA, Schlam TR, Cook JW, Fiore MC. New methods for tobacco dependence treatment research. Annals of Behavioral Medicine. 2011;vol. 41:192–207. [PMC free article] [PubMed]

4. Schlam TR, Baker TB. Interventions for Tobacco Smoking. Annual Review of Clinical Psychology. 2013 Mar;vol. 9:675–702. [PubMed]

5. Whittaker R, McRobbie H, Bullen C, Borland R, Rodgers A, Gu Y. Mobile phone-based interventions for smoking cessation. Cochrane Database of Systematic Reviews. 2012 [PubMed]

6. Free C, Phillips G, Galli L, Watson L, Felix L, Edwards P, Patel V, Haines A. The Effectiveness of Mobile-Health Technology-Based Health Behaviour Change or Disease Management Interventions for Health Care Consumers: A Systematic Review. PLOS medicine. 2013 Jan [PMC free article] [PubMed]

7. Ajzen I. The Theory of Planned Behavior. Organizational Behavior and Human Decision Processes. 1991;vol. 50(no. 2):179–211.

8. Norman P, Conner M, Bell R. The theory of planned behavior and smoking cessation. Health Psychology. 1999 Jan;vol. 18(no. 1):89–94. [PubMed]

9. U.S. Department of Health and Human Services. Ending the Tobacco Epidemic: Progress Toward a Healthier Nation. Washington: U.S. Department of Health and Human Services, Office of the Assistant Secretary for Health; 2012. Aug,

10. Grimshaw GM, Stanton A. Tobacco cessation interventions for young people. Cochrane Database of Systematic Reviews. 2006;vol. 18:4. [PubMed]

11. U.S. Department of Health and Human Services. The Health Consequences of Smoking: A Report of the Surgeon General. Atlanta: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Chronic Disease Prevention and Health Promotion, Office on Smoking and Health; 2004. [Retrieved on March 11, 2013]. from: http://www.cdc.gov/tobacco/data_statistics/sgr/sgr_2004/index.htm.

12. Wikipedia. Text messaging. [Retrieved on March 11, 2013];Wikipedia. from: http://www.wikipedia.org/wiki/text_messaging.