

An mHealth Recommender for Smoking Cessation using Case Based Reasoning

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Abstract

The possible cause of many life-threatening diseases such as lung cancer and cardiac myopathy lies in the addiction to tobacco. Apart from being responsible for premature deaths, early diseases and reduced immunity, smoking also inhibits physiological and psychological problems in children born from addicted mothers. Though many developed countries have consciously made efforts to curb smoking, for the developing countries, the trend is still on the rise. The promising factor is that there are many people who are willing to quit smoking and are resorting to technology and electronic media for the same. In this paper, we have proposed a unique smoking intervention plan with the help of mobile phones that uses a Case Based Recommender system. Our model resorts to generating finely customized motivational messages depending on the patient profile and delivery of the same via mobile phones.

1. Introduction

Addiction to smoking is becoming a rampant problem globally and is the cause of many diseases including lung cancer, heart diseases and respiratory problems [1]. The effects can be psychological as well as physical. One of the major causes of premature deaths and disease worldwide is tobacco smoking. Globally, approximately 1.3 billion people currently smoke cigarettes or other tobacco products [2]. While smoking rates have leveled off or declined in developed nations, in developing nations tobacco consumption continues to rise at a rate of around 3.4% per annum. Around 80% of the world's smokers live in low and middle-income countries [3] and more than 6 million people worldwide die due to tobacco consumption [4]. Asia, which contains around 60% of the world's population, has more than half the world's smokers. In fact the smoking prevalence in Japan, China and Vietnam as compiled by WHO in 2010 are 38%, 53% and 47% respectively [5].

The rising costs of healthcare have been a stimulant for people to take better precautions against

likely diseases. The cost of personalized healthcare is often a barrier for people seeking specialized care for issues like smoking addiction. This has thereby prompted people to explore web-based technologies [6] that have been cost-effective, resulting rapid proliferation. Initial studies [7] show that innovation in delivering computer-based health-interventions for smoking cessation indeed has potential.

Effective intervention mechanisms call for a proper delivery medium. At the same time, mobile phones have been a ubiquitous medium of communication both in developed as well as developing countries [8]

Table 1 – Global mobile Cellular Subscriptions, 2011

Key Global Telecom Indicators for the World Telecommunication Service Sector in 2011 (all figures are estimates)			
	Global	Developed nations	Developing nations
Mobile cellular subscriptions (millions)	5,981	1,461	4,520
Per 100 people	86.70%	117.80%	78.80%
Source: International Telecommunication Union (November 2011)			

Currently there are 3.3 billion mobile-phone users globally and this makes it a very convenient platform to spread awareness. The global mobile phone subscription statistics in Table 1 shows the potential outreach of this platform. In fact, mobile based messaging systems [9-13] have already experienced acceptability when backed by the motivation to undertake certain behavior changes. Such interventions range from informational mass-weekly messages [14] to tailor-made customized messages [15] based on user-input, but a few shortcomings have been observed. Firstly, customizations were based on user-input and not on user-habits or user-behavior. Secondly, such customizations didn't take into account the user profile such as demographics, age and sex. Finally,

without any feedback from users, the system couldn't adapt or adjust its strategy.

In order to address these issues, we propose a Hybrid case-based recommender (HCBR) for motivational message delivery through mobile phones and apply it in a smoking cessation program. These messages are graded in three intensity levels, namely normal, medium and high. These messages may include the names of friends and family picked from the user profile information and how the user's behavior might affect them. The HCBR uses a graded evaluation strategy in sending messages to users. The first alternative is to locate similar cases from the case database, taking into account the demographics, age and sex. Adding an intensity function from user's craving patterns basing on his target wellness timelines further refines this. This tries to pacify the user's current craving by means of the customized normal or medium intensity messages. In case the first intervention fails, the second alternative is to follow-up with a high-intensity message. The third and final intervention is to put the user through an automated voice call as a last mean to refrain the user from smoking. The proposed method is, to the best of our knowledge, the first mobile-based intervention that uses the case-based recommender system technique to personalize motivational messages.

The paper is organized as follows. Section 2 gives a brief background to the problem in hand. In Section 3, some supporting real-life cases that use mobile phones as an intervention medium are being discussed. Section 4 elaborates the choice of a recommender System for smoking-cessation. Section 5 discusses our proposed-model based on the case based recommender. In section 6 we discuss the implementation details of the system. In section 7 we discuss the evaluation techniques and in section 8 we discuss the limitations and future scope of the system. We conclude the paper in section 9.

2. Background

More than two thirds of the world's smokers live in just 10 countries (WHO)[16]: China, India, Indonesia, Russia, US, Japan, Brazil, Bangladesh, Germany, Turkey.

Table 2 shows the smoking prevalence in these countries while Figure 1 shows the high prevalence of adult tobacco users in developing countries.

Table 2 – Estimated Smoking Prevalence in Countries

WHO age standardised estimated prevalence of smoking among those aged 15 years of more			
Country	Income Group	Cigarettes (Current)	
		Male	Female
China	Middle	50	
			2
		Total	26
India	Middle	11	
			1
		Total	6
Indonesia	Middle	57	
			4
		Total	30
Russia	Middle	59	
			24
		Total	41
US	High	28	
			24
		Total	26
Japan	High	42	
			12
		Total	27
Brazil	Middle	21	
			13
		Total	17
Bangladesh	Low	28	
			<1
		Total	14
Germany	High	33	
			25
		Total	29
Turkey	Middle	46	
			14
		Total	30

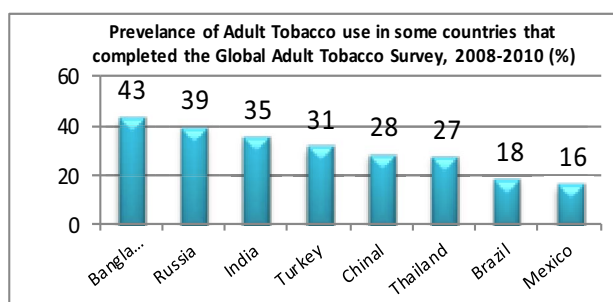


Figure 1: Country wise prevalence of Adult Tobacco Use (in %)

In China, between 2000 and 2009, the total spending on tobacco quadrupled to US\$28.9 billion from US\$7.2 billion and in Bangladesh, direct costs of smoking are estimated at US\$386 million. Furthermore, between 2003-2008, 11.3% of Egypt's total health expenditure was used to treat tobacco-related illness [17].

Many countries have a very high direct as well as indirect cost to smoking and this is on the rise. At the same time, according to the GATS 2008 to 2010 survey (figure 2), a large percentage of smokers plan to quit smoking. In developing countries like Bangladesh and India, this is as high as 68% and 47%. In developed countries, such as in the UK, Smoking causes a large and growing number of premature deaths[18]. According to a study[19], 38.4 per cent smokers -- 38.3 per cent men and 38.9 per cent women -- have made an attempt to quit. In a continent like Australia, of the 4.5 million smokers, 3 million want to quit with about 1 million trying to quit each year. The potential outreach of mobile technology can play a vital role in extending healthcare support and services to populations living in even the remotest of locations.

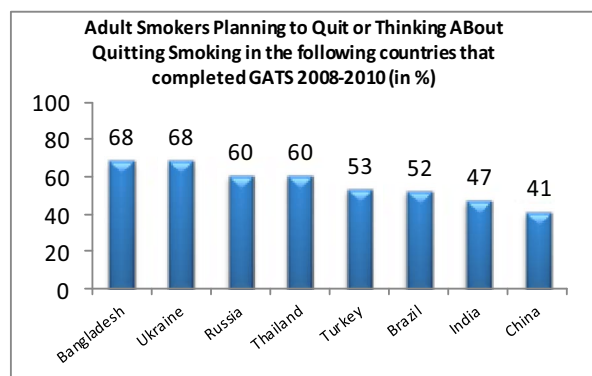


Figure 2: Percentage of smokers planning to quit smoking in different

3. Smoking Cessation Interventions

According to a study by Riley et.al. [20], the use of mobile technology for health interventions can help in bringing about sustainable behavioral changes. In a study “*Text 2 Stop*” also popularly known as “*Text2Stop*” program conducted in the UK, the effect of automated mobile messages for smoking cessation was observed. One intervention group was randomly allocated to a mobile text smoking cessation program and they were sent motivational as well as behavioral-change support messages. A control group was sent mobile text messages that were totally unrelated to quitting. The results indicated that continuous abstinence was significantly increased in the intervention group by almost 10.7% compared to the 4.9% of the control group. In a similar program *Text2Quit*, a smoking-cessation intervention was carried out that involved sending both emails and text-messages to participants over a

period of 3 months around a quit date. Pre and post-quit educational messages, peer ex-smoker messages, medication reminders and relapse messages were sent. Participants were surveyed at baseline and then at an interval of 2 and 4 weeks respectively. It was found that most of the participants liked the program after the 2 and 4-week timeline (90.5% and 82.3%, respectively) and supported text messages more than emails. Around 75% read most or all of the text messages.

In a study for College-Smokers [12], an attempt was taken to quit smoking through tailored specific messages over a period of 6 weeks. Study post the experiment confirmed good acceptance of text-messages and showed 45% abstinence. In [13], a trial intervention group was given regular, personalized text messages providing smoking cessation advice, support and distraction for 6 months. The results showed that around 28% of the participants had quit at six weeks in the intervention compared to the 13% of participants from the control group.

4. Hybrid Case Based Recommender System for the Smoking Cessation problem

The study of recommender systems came in the light of providing meaningful recommendations to users those who generally have too many items to choose from. Of late, the scope of Recommender Systems and popular collaborative filtering techniques have been gaining acceptance from both academia as well as the industry. While recommender systems are still most popular over the e-commerce domain, there have been many offshoots where people have used the concept to get recommendations on a host of subjects such as travel, food etc.

Recommender Systems used as an enabler in health intervention brings forth novel functionalities [21] e.g. based on the patient’s reported data, a recommender system can guide the patient about the necessary clinical tests that needs to be done. M. Wiesner and D. Pfeifer [22] has shown a method where, by exploiting the existing semantic health network, a health-graph is constructed. The nodes of such a graph contain information that can be compared against a particular user’s health-graph and necessary health recommendations can be suggested. Zanker [23] has simplified the method of evidence collection by constructing rule-based preferences from historical data.

One of the pre-requisites of any Recommender System is ‘profiling’. The Recommender System initially spends some time in gathering experience about a particular user and only then can it start producing recommendations. Thus, without proper profiling or user knowledge, the recommender system is almost blind. This limitation of Recommender Systems is particularly evident in the case of a Cold-Start problem [24]. In a Cold-Start case, when there is little or no information about a particular user, it becomes almost impossible for the recommender system to propose a solution. Case Based Reasoning on the other hand tries to draw conclusions from existing cases that it has already encountered and further tries to adapt existing solutions to newer results

In this paper, we have resorted to the use of a case based reasoning methodology to provide intervention recommendation to the users. Here each demographic setting is a scenario and each user is an actor. The intervention logic is chronologically recorded with a feedback mechanism that is obtained from the craving pattern of the users. This feedback and the prior history of successful cases make way for exploration of newer cases.

5. Proposed Model

The proposed model has a set of pre-compiled message templates and such messages are guided from researches in behavioral psychologists. The message intensity is divided into three categories, namely: normal, moderate and strong. In case of normal intensity messages, the contents are quite generic and mainly informational. E.g.: “You can also stop smoking”, “Smoking kills your body and cleans your bank”, “Last year 5 million people had respiratory issues caused by smoking”. These messages are applicable for anyone who wants to quit smoking. The moderate intensity messages are a little personalized whereby the performance of the candidate is also included as part of the message. This might include the participants’ craving frequencies or how other participants who belong to a similar profile as him are performing. These messages are mostly generic with some additional personal statistics. The third category of messages is of an emotional type. Here the message templates are pre-defined with inputs from the user during the registration phase. The normal messages are intensified with specific user given agendas. Let’s say for example user Joe, who aims to quit smoking while registering had put in the following two events as the most important things he would like to accomplish in his life in near future:

Important events in next few years	Your role in the important event
Harvey graduates from college in 2 year	Make Harvey smile by attending the convocation ceremony
Alice gets married next year	Stand like a proud father

The motivational messages are constructed considering these parameters in mind. Examples of such messages are:

- “Harvey graduates from college in 2 years. Smoking kills. Make Harvey smile by attending the convocation ceremony”
- “Alice gets married next year. Be healthy and happy, stop smoking. Stand like a proud father”
- “Harvey graduates from college in 2 years. Last year smoking caused 1.5 million lung cancers. Say no to smoking. Make Harvey smile by attending the convocation ceremony”

The personalized messages are constructed by including a regular message in between the important event and the user’s role in the important event. Such emotional messages form a part of the personalized therapy for the user.

At the heart of our model lies the case engine. At the onset, the case-engine starts with the smoking statistics by country and risk factor measures in terms of percentage mortality from smoking only. The mortality rates are arranged in decreasing order and the top 33% are marked candidates for severe-risk, the next 33% marked as moderate risk and the rest as low-risk. When someone signs up for the program, depending on the ethnicity and sex, they are placed in the corresponding zone at the very beginning. This completes the initial model setup part.

During execution, the subscribers are sent motivational messages periodically. The message category depends on their classification at the beginning, which is based on the ethnicity and sex. Once the messages begin rolling, the user feedback is noted. In this case, the feedback is a CRAVE message that can be sent by the user to a toll-free number. The feedback is stored along with the number of messages of each type that are sent to the users. This information is stored in the case-database against the given profile, along with the message list and types of the message. A crave-index is built at the end of the assessment period using following formula:

$$crave - index = \frac{3 * \text{strong-messages} + 2 * \text{moderate-messages} + \text{normal-messages}}{\text{total number of times the user pressed crave button}}$$

At every assessment period, the crave index is compiled for all users. If no-crave button is pressed during a particular period, the crave-index is taken as the total-number of messages sent, irrespective of the message type. This assessment period can be weekly, fortnightly or monthly depending on how the user wants his feedback recorded and the timeline allowed for the program. The crave-index is arranged in a descending order and the top 25% people are considered to have a very high craving. They are then sent strong-messages till the next assessment period. The next 25% of candidates are sent strong or moderate intensity messages guided by a certain probability given by the following formula:

$$\text{crave-ratio} = \frac{\text{sum of crave-index of belonging community}}{\text{total crave-index across all users}}$$

A number between 0 and 1 is drawn at random. If the number is less than the crave ratio, a moderate intensity message is sent, else a strong intensity message is sent. A similar policy is followed for the next 25% candidates where they are sent a moderate or a normal intensity message based on probability. Candidates who have a crave-index in the bottom-most quartile are the ones who have the least craving and are sent only normal messages.

The crave-index is monitored using a sliding window [25] with three-week time-frame. If the assessment period is three-week, then the sliding window coincides with the evaluation frame. At every sliding window, the crave-index is computed. If the value remains similar to earlier indexes, the same messaging pattern is continued. However, if the value shows an increasing-trend, the message-frequency is immediately doubled. On the other hand, if the crave-index shows a decreasing pattern, the messaging frequency is reduced by a small fraction. At the end of every assessment period, the aggregate crave-index is calculated and the behavior is plotted against a graph. As long as the crave-index shows a decreasing trend, we assume that the model is working fine. If the crave-index increases in the last few assessment cycles or the value does not change, we infer that the intervention needs a boosting. The HCBR then looks for people with similar but consistent crave-index while considering ethnicity, smoking frequency at the start of the program, age and sex. If an exact match is not available, we adopt a constraint based collaborative filtering technique like

the one suggested by Zanker[23] to get a close match. Once the system is able to identify a set of fellow candidates, one such profile is picked at random and the intervention messages along with message frequency is mimicked till the next assessment cycle. In case the selected profile contains many emotional or strong intensity messages, the message template is finalized while the contents are replicated from the patient's own profile.

The procedure or intervention cycle described above is repeated till the crave-index starts showing a decreasing trend or the change is very little.

The highlight of the model is as follows:

- If the diagnosis is correct in the sense that the adoption of the intervention has decreased the patient's craving, it is considered to be a successful case and is entered into the case database
- If the diagnosis fails initially, there is always hope that an alternate route from the case database from similar profiles can be obtained.

This recommender update logic is shown in Figure 3.

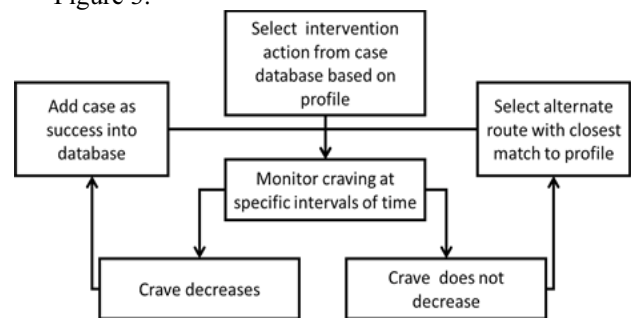


Figure 3. Recommender update logic

6. Implementation Details

In this section we shall discuss the design details of the proposed solution.

6.1 Study Design

The study will include a quantitative analysis of the effectiveness of a SMS based mHealth service that will monitor and help in smoking cessation across two different geographies- India and Australia. Up to 600 participants from India and Australia will be recruited for the study for a period of 24 weeks. The criteria for participant selection will include the following:

- Aged above 18 years
- Smoking at least 1 cigarette a day
- Has access to a mobile phone

- Can read and respond to SMS
- Can provide informed consent
- Wants to quit smoking

Program advertisement will be carried out through word of mouth, online social media groups, banners and posters, municipality supported health centers and hospitals, doctors' associations and emails. For a randomized control trial, the participants will be divided into 3 groups. The control group (group 1) will not receive any message but will be surveyed at the end of the assessment period. Experiment group 2 will receive only generic messages and not be influenced by the recommender system while experiment group 3 will receive personalized SMS through the recommender system based on ethnicity, sex, age group, and nicotine dependency.

Table 3. Baseline Survey Questionnaire for Participants

1. Name
2. Age
3. Sex
4. Ethnicity
5. Employment Status
6. Number of children in the home: 1/2/3 or more
7. Health care coverage: No healthcare coverage/Healthcare coverage by employer/Personal healthcare coverage/other
8. How many cigarettes do you smoke each day
9. For how long have you been smoking?
10. By when are you planning to quit? : 1 to 6 months/6 to 12 months/ more than 12 months
11. Name two most important events planned in the next few years and the main people involved in these events
12. Who are the most significant persons in your life? Parents/Partner/Spouse/Children/Others
13. Why do you want to quit smoking?

Table 3 contains the questions for the baseline survey, which have been selected to gather required information from the participants to fit our model design. These questions along with the Fagerstrom test for nicotine dependence[26] need to be filled in by participants at the start of the program. The recommender system will then group the participants according to their age, ethnicity, number of cigarettes they have smoke and the period of time they have been smoking for.

6.2 Message Design

As mentioned earlier, the messages that will be sent to the participants will be grouped into 3 categories - normal, moderate and high intensity. Normal intensity messages will be generic and informational in nature and will be similar to messages that were used for earlier successful SMS based smoking cessation interventions[11]. Some examples of the messages used in existing literature are given below-

- "This is it! - QUIT DAY; throw away all your fags. TODAY is the start of being QUIT forever, you can do it!"
- "To make things easier for yourself, try having some distractions ready for cravings and think up some personal strategies to help in stressful situations"
- "Why not write an action list of your reasons why you want to quit. Use it as your inspiration."

These types of messages will belong to the normal intensity message group.

Moderate intensity messages will motivate the participants by including their performance in the messages. For e.g. "Hey Richard, your average craving per day has reduced by 40%! You are almost there. Great job and keep going."

High intensity messages will include personal data that was collected from the participant during the baseline survey. It will refer to the people who matter the most to them or some very important event in their life to harp on the emotional side of the participants and motivate them to quit. Examples of high intensity messages would be "Your wife Jane needs you. Smoking can take away quite a few years from your life. Quit smoking and bring more happiness to your wife!" or "You do not want Mike to be a passive smoker do you? Make your kid's life healthier and quit smoking."

6.3 Workflow

The intervention process starts with a person signing up to the program. During the sign up process, the person fills up a questionnaire (Table 3) which gives the system an idea about the person's smoking habits and creates a patient profile which is stored in a database. Once signed up, the person can interact with the system through SMS (Fig 4), either manually or through a smart phone interface. These messages can be of two types – 1. Predetermined keywords like "CRAVE", "HELP", "QUIT", etc. 2. General queries.

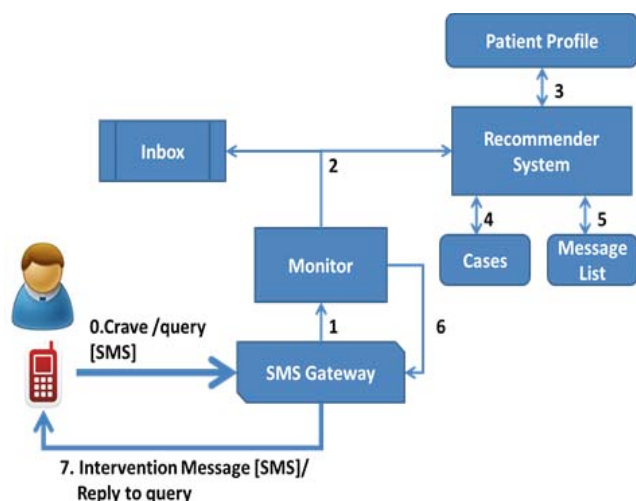


Figure 4. System workflow

The SMS is received through a SMS Gateway and forwarded to a monitor that parses the text and determines the type of message. In case of a general message or query, the message is simply stored in the inbox and can be viewed by the staff and replied to. On the other hand, if the message contains a keyword like CRAVE, the monitor forwards the message to the recommender. The recommender matches the phone number with the patient profile and compares it to a set of cases in the Cases database. Based on the type of case, the recommender fetches the appropriate message and forwards it to the monitor, which in turns uses the gateway to send the message to the person.

6.4 System Architecture

The system is built on the AMP (Apache, MySQL, and PHP) platform, which is completely open source and reduces development cost. The monitor and recommender are built using PHP while all the databases are stored in MySQL. The interface for the service provider is browser based and designed using HTML, CSS and JavaScript. Figure 5 shows the overall architecture of the system.

The client (patient) uses the standard SMS interface provided on their phone or a smart phone interface to interact with the system. The smart phone interfaces are supported only on android and iOS and makes the interaction simpler.

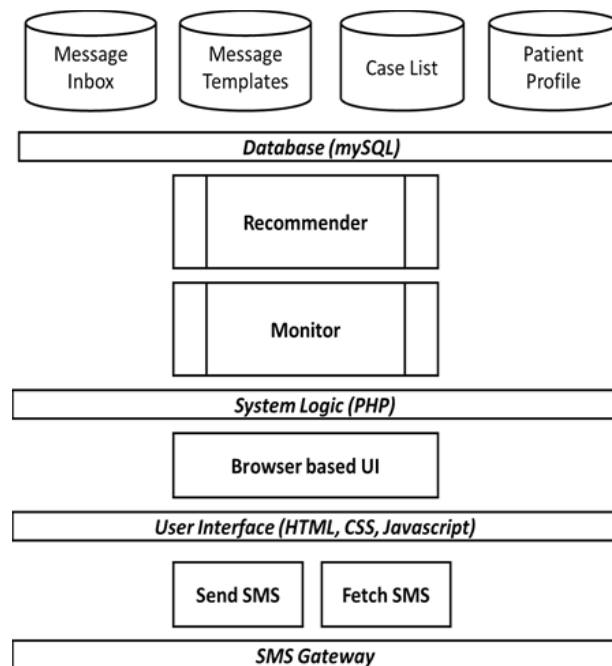


Figure 5. System Architecture

6.5 System Components

1. Databases-

Patient Profile – The patient profile database contains the list of subscribers enrolled in the program along with their smoking habits and usage patterns. The recommender makes the intervention decisions based on the information available in this database and matching them with the cases available in the case list database.

Case Database – The case database contains the profile of all the users who went through the system. It contains successful as well as failed cases. The biggest advantage of the Case Database is that the case-history is in a chronological format. This makes it easier to find out the intervention patterns of both successful patients as well as failed patients. During the course of intervention, the successful cases, their crave-index and number of weeks into the program act as a guideline to suggest suitable recommendation patterns. Every current user activity along with the crave-index and the intervention details are continuously updated in the database.

Message Templates – The message template database contains the complete list of SMS messages that are used for the intervention.

Based on the patient profile and matching cases, the recommender fetches the appropriate message and personalizes it for the patient.

Message Inbox – The message inbox database contains queries sent by the subscribers for the intervention team to respond to. The monitor populates this database by automatically filtering out messages that are only keywords like “CRAVE” and “QUIT”.

2. *Monitor*

The monitor is the main controller of the system. It receives the SMS from the gateway and parses it. Depending on the content of the message, it either stores the message in the inbox or takes an appropriate action based on the keyword e.g. If the keyword received is “CRAVE”, it calls the recommender to generate an appropriate intervention strategy. The monitor also forwards the generated or response messages to the SMS gateway, which in turn sends the message to the subscriber.

3. *Recommender*

The Recommender system works as per the design outlined in Section 5. The sliding window length is 3 weeks and the crave-index is calculated at a weekly interval. When the crave pattern remains almost constant or has an increasing trend, similar user cases are consulted and their message attributes are replicated. If crave shows a decreasing trend, the system infers that the intervention is working properly.

4. *SMS Gateway*

The SMS gateway is simply a tool to send and receive SMS messages. Multiple providers provide APIs for online SMS delivery and retrieval. The monitor is linked to these services using their APIs and continuously monitors them for incoming messages. In order to send an SMS, the monitor packs the message in the format specified by the service provider and forwards it using the APIs.

7. Evaluation

The evaluation of the recommender system for smoking cessation will be carried out 6 weeks from the date of project initiation. As already described in the study design, participants will be divided into three equal groups

- Group I (Control) – The control group will not receive any motivational or support messages at any stage of the program.
- Group II – This group will be sent only generic informational or motivational messages
- Group III – This group will receive messages that are dynamically customized by the recommender system based on their profile and crave patterns.

At the time of enrollment into the program, all participants will need to complete a baseline survey which will include the Fagerstrom test for nicotine dependence [26]. At the end of 6 weeks, the Fagerstrom test will be carried out again to determine if there is any change in smoking habits. Based on the two sets of data amongst the three groups, the most important measures that will be calculated are–

- Percentage of participants who have reduced smoking (categorized by age, sex and ethnicity) under each group
- The average reduction in cigarette consumption (categorized by age, sex and ethnicity) under each group
- Percentage of participants who have quit smoking (categorized by age, sex and ethnicity) under each group

8. Discussion

8.1 Generalizability

This particular model has a potential of being used not only for smoking cessation but also other similar behavioral change interventions like fighting obesity. The model could also be used to assist in promoting drug adherence and improving motivation amongst patients suffering from chronic diseases like tuberculosis and HIV from whom simple SMS based messaging tools are already being developed [27]. With its easy dissemination and high efficacy potential, it can be widely used as the basis for many other mobile based health services and can be converted into a cost effective and readily available health service especially in developing countries.

8.2 Limitations

This model currently tracks only the crave patterns of subscribers as feedback and there is no way in which the cause and situation of the craving can be identified. This information could have potentially prompted more personalized messages. Secondly, the model uses only successful cases while

attempting to find a solution. Previous cases of failure are not considered. The context of failure and in-depth analysis can lead to a better recommender system.

Presently, the system is designed to work using English as the communication language and therefore people who do not understand the language cannot be included in the study even though they are in considerable numbers especially in developing countries. Once the initial system is tested, future designs could support messages in multiple local languages by using a model similar to that proposed by Bakshi et.al. [28].

As is the case with similar intervention programs, the onus finally lies with the subscribers and there is no fool-proof way to determine if the feedback being provided by the person is true or not.

8.3 Future Work

Currently the generic motivational messages used in our intervention system uses messages from existing successful smoking cessation programs, but a review carried out by Riley et al. [20] shows how self-observation, self-evaluation, and self-reaction processes of Self-Regulation Theory can be used for making these interventions more interactive and adaptive. Saha et al. [30] introduced a heuristic that can adopt preferences with the user's changing behavior. Some of the techniques described can be leveraged further in our model and used for making the recommender system based smoking cessation intervention more interactive, effective and dynamic.

Secondly, the major challenge of accurately translating messages into other languages to attract larger audiences can potentially be solved through crowdsourcing[29] - a community based technique, used most prominently by Facebook, where members of the community carry out the task of translating messages while other members validate the correctness of these translations before they are finally used by the system. Thus, crowdsourcing can provide a cost-effective yet reliable way of delivering the service to larger demographics.

9. Conclusion

In this paper we have introduced a smoking cessation intervention program that uses a personalized recommendation system to motivate subscribers to stay away from cigarettes and control the urge to smoke during their quit phase. The program uses existing behavioral data of smokers and a list of messages to intelligently send motivational

cum support messages via mobile text messages to subscribers. Some additional features like participant specific motivational/support messages and case based recommender technique will be introduced for the first time in the system that will help in making the abstinence rate in this smoking cessation program better. Based on the success of earlier mobile phone interventions, we hope the introduction of an intelligent and personalized system will further motivate people to quit smoking. The actual success of the system remains to be seen and future study will look into the success and issues with the practical use of such a system.

10. Acknowledgement

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