Effects of Coaching on Adherence in Remote Health Monitoring Systems

Analysis and Prediction of Participant Adherence

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ABSTRACT

Among all of the major organizations, including the World Health Organization, the Centers for Disease Control and the Pew report the focus on disease prevention is critical. Given the rapid advances in technology it has become clear that there is a critical role for remote health monitoring systems (RHMS) in the prevention of chronic disease. The number of interdisciplinary clinical trials has increased over the past few years. In preventive medicine RHMS are designed to reinforce patient education, monitor and insure participant adherence, and provide a means of communicating information to the clinician. In this paper we examined data collected from a smartphone-based RHMS intervention for young Black women at risk for cardiovascular disease. The goal of the intervention was to improve cardiovascular risk factors through classroom-instituted self-management education on risk factor reduction in an attempt to change behavior over time. To augment the classroom education we created a means of remediation and social support through wireless monitoring and coaching creating a sense of "connectedness". This paper reports the effects of RHMS automated messages, clinician text messages and clinician phone calls in improving adherence to the study protocol. Typically participants with low adherence maintain low adherence, and participants with a high level of adherence maintain a high level of adherence. We examined the effects of messaging on adherence from one week to another and show that prior week adherence is a valuable predictor of the following week's adherence level. Our findings show that RHMS messages are successful in motivating the group of participants that are inconsistently adhering to the study regimen. We also show that it is possible to predict weekly participant adherence with high accuracy.

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Categories and Subject Descriptors

J.3 [**Health and Medical information systems**]: LIFE

Keywords

Experimentation, Human Factors, Algorithms

1. INTRODUCTION

Despite efforts in health care and prevention, Cardiovascular Disease (CVD) remains the leading cause of death in the United States. Statistics from the American Heart Association show that more than 2,150 Americans die each day of CVD [14]. In 2009 CVD was responsible for 31.3% of the total deaths in the U.S. This translates to an average of 1 death every 40 seconds. A similar situation exists in Europe as well, where recent statistics in the European Heart Journal [17] attribute almost 4.1 million deaths per year or 46% of all deaths to CVD.

The reasons for the high prevalence of CVD can be traced to the increased proportion of the population that have one or more risk factors for CVD at a very young age. An estimated 31 million US adults exhibit cholesterol levels above $240mg/dL$. Additionally, 32.6% of US adults above 20 years of age have with hypertension. Finally, 10% of US adults are affected by Diabetes Mellitus and an alarming 35.3% have prediabetes: a condition characterized by abnormal fasting glucose levels. There is a high propensity of hypertension and diabetes in the Black community and a higher rate of morbidity and mortality from CVD.

The Women's Heart Health study presented in this work focuses on Black women, a particularly vulnerable part of the population. In fact, CVD related deaths were 32.1%

higher for Black females than white women (248.6 deaths per 100000 vs 188.1). A remote health monitoring system (RHMS) Wanda-CVD, was deployed to monitor the effects of education and social support from automated and clinician messages and coaching on reducing risk factors for CVD. In this paper, we focus on the intervention group and evaluate the relationship between automated/ clinician coaching and distal effects of adherence to the study protocol from one week to another. We further design a framework to predict weekly participant adherence to optimize clinician intervention by informing them about participant future adherence. We hope to further validate our systems predictive power and the proximal effect of our treatment through micro-randomization of messages in future trials [11].

This paper is organized as follows. Section 2 discusses background and related works. Section 3 discusses the Women's Heart Health Study and the deployment of automated and clinician messages in Wanda-CVD. Section 4 describes the methodology used in analyzing the collected data. Section 5 provides the results and discussion. Finally, we conclude and discuss future work in Section 6.

2. BACKGROUND AND RELATED WORKS

While CVD is the number one cause of death globally, research has shown us that lifestyle changes are the key to reducing risk factors for CVD. Increased physical activity is among the top three factors for CVD risk reduction along with eliminating exposure to tobacco and maintaining healthy eating habits [7]. Class 1 recommendation guidelines for stroke prevention focus on diet and exercise especially in participants at high risk for stroke. Studies have shown that black women have a particularly high risk of stroke [5]. Intervention trials that focus on behavior change have initially been successful however have not stood the tests of time. This is based on the premise that a mobile phone application that focuses on coaching and motivation, along with self-monitoring and an opportunity to link social support might improve the user's self-monitoring experience and adherence to a physical activity program [3].

To address this, a variety of RHMS studies have shown positive outcomes. Antonicelli et al. [4] demonstrated both reduced mortality as well as reduced readmission rates for congestive heart failure patients in RHMS. Morguet et al.[13] reports a 50% reduction in hospital admissions (38 versus 77/100 patient years, $P = 0.034$) and 54% reduction in hospital length of stay for congestive heart failure patients. Several studies reported that compared to usual care, patients with diabetes and hypertension that receive RHMS resulted in improved glucose control, cholesterol, and blood pressure [18, 20, 1, 16, 12]. Two meta-analyses [22, 9] of RHMS found that patients with heart failure that receive RHMS have a 7% and 42% reduction in hospitalizations respectively. Moreover, comparative studies performed on 17,025 patients enrolled in the Veterans Affairs (VA) home monitoring program in 2006 and 2007 show a 25% reduction in bed days of care, 20% reduction in readmissions, and a satisfaction score of 86% [6].

Mobile health approaches are also found to be useful in several applications including child obesity prevention [21]. Spring et al. show that remote coaching supported by mobile technology and financial incentives significantly changed behavior, increasing daily fruit/vegetable intake and decreasing sedentary leisure and saturated fat [19]. In our study we would like to show the impacts of remote coaching on mobile technology and report correlations to adherence of the study protocol.

3. STUDY & RHMS DESIGN

3.1 Wanda-CVD RHMS

To carry out the study, we relied on an improved version of a previously developed RHM system named Wanda [10]. We expanded the original RHMS to incorporate an increased sense of "connectedness" between participants and clinicians and by introducing Wireless Coaching. Wireless Coaching in Wanda comes in the form of automated messages (push messages) reminding the participant to commit to certain actions related to the goal of the study and clinician messages (either through text messages of phone calls).

The complete Wanda-CVD system is outlined in Figure 1. Data from participants are collected on an Android-based smartphone application. Using embedded sensors, Bluetooth and Wi-Fi/Cellular network technology, the smartphone application can be programmed to connect to many stand-alone patient monitoring systems. The application also receives and displays Wireless Coaching push messages. This information is transmitted securely to a backend server, where it is stored and machine learning algorithms process the data to identify patterns and learn patient models. The final component is a web-based portal that provides clinicians with a visual cue and summary of what is happening with each participant, alerting them when a matter requires their attention.

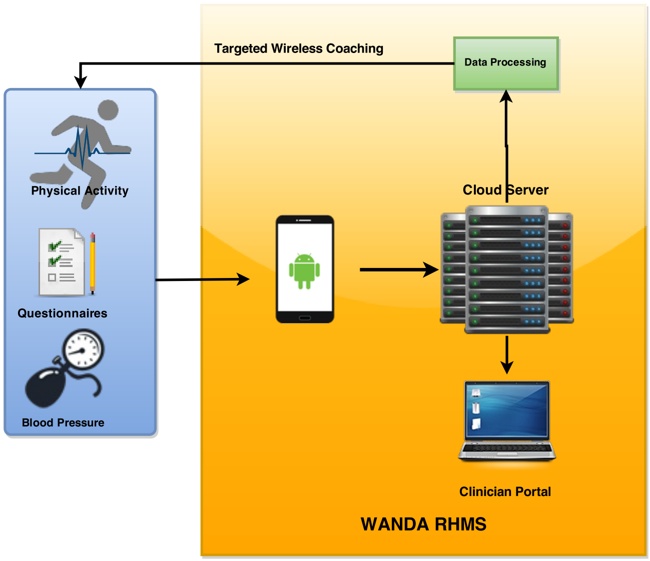

Figure 1: Wanda-CVD architecture diagram

3.2 Women's Heart Health study

The Women's Heart Health Study is a UCLA IRB-approved study of 90 young black women aged 25-45 years that have a minimum of two risk factors for CVD. Randomization occurred at the beginning of the study and the participants were randomized by church upon entry into the study. Wanda-CVD was deployed to analyze the effects and lifestyle changes that result from social support via wireless coaching. In addition to the data collected from Wanda-CVD during the study, the participants also completed baseline screening of cholesterol levels, blood pressure, BMI, demographic and psychosocial questionnaires and received educational classes. Each of the intervention group participants received nutrition and lifestyle education, along with a Bluetooth blood pressure monitor and a smartphone with Wanda-CVD preloaded. Clinicians instructed the participants to wear the smartphone around their waist to detect their level of physical activity throughout the day. The participants were monitored for a period of 6 months and were requested to respond to daily and weekly questionnaires. Through the smartphone, participants received 12 daily questions spread out over 6 days (weekdays and Saturday). They also received 12 weekly questions (answered on a single day, typically a Sunday). Finally they were asked to measure their systolic and diastolic blood pressure twice in one sitting per week. The intervention group also received wireless coaching messages, and in this paper we attempt to study the weekly distal effects of messaging on study protocol adherence.

3.3 Automated Wireless Coaching Messages

There are four categories of automated wireless coaching messages defined in Table 1: inspirational, daily questionnaire, weekly questionnaire, and blood pressure related messages. One out of seventeen inspirational messages is pushed to a participant every other day as a means of reinforcing the education received during baseline. The system also analyzes the participants' adherence to the study protocol and accordingly pushes targeted coaching messages designed to improve adherence. If the user forgets to take a measurement on a particular day the system would send them a corresponding daily questionnaire, weekly questionnaire or blood pressure reminder the following day. Table 1 provides a list of the automated messages participants in the intervention group received over the course of the study.

3.4 Clinician Messages

In addition to the automated coaching provided by Wanda-CVD, a clinician specialized in cardiovascular disease and a kinesiologist met weekly to review the progress of each participants' blood pressure, physical activity level, and adherence to the daily and weekly questionnaires. Following the weekly review, clinicians selectively contacted participants by phone or text messages and provided personalized education to encourage them to adhere to the study protocol (Clinician Adherence), or discuss their BP measurement (Clinician B.P.), or provide a means of positive reinforcement if all is going well (Clinician Positive Reinforcement). Table 2 displays the three different categories of clinician messages.

4. METHODOLOGIES

The objective of this work is to study the effects of clinician-participant coaching in improving participant adherence. In this section we first define how we quantify adherence and how we process the messages. Then we discuss the data analysis techniques used to generate the results in the following section.

Table 1: Automated Messages

Daily Questionnaire Reminders
Self-care is the task of taking care of your health every day.
Self-awareness starts with you. Remember to take the daily questionnaires.
Have you been completing the daily questionnaires? Healthy living starts with education and learning.
Inspirational Messages
Breathe in through your nose and become aware of your breathing. Breathe easy.
Don't allow anyone to pollute the air your breath.
Exercise increases your energy level - take a light walk around the neighborhood.
Reduce your stress by laughing or just relaxing - tension and anxiety is lowered
Try a new fruit or vegetable today.
Take a walk with a friend today - light walking is considered a light-leveled activity.
Go outside and enjoy the fresh air for a few moments.
Even a small amount of physical activity is better than none.
Small changes over time = :)
Deeply relax all your muscles, beginning at your feet and going all the way to your face
Increasing your physical activity level strengthens the heart and the lungs.
Take some time for yourself - relieve stress and take a nice walk.
Keep going, you can do it - give yourself a pep talk.
Every day you increase your activity you help your body burn fat.
Be active, be a role model for your children/family!
Put a little pep in your step!
Take the steps today and reduce your risk for heart disease.
Weekly Questionnaire Reminders
Self-care that focuses on heart health is a powerful way to decrease your risk for heart disease.
Keep yourself healthy = keeping your families healthier
People who take care of themselves are better equipped to take care of others. Remember to complete your questions.
Blood Pressure Reminders
Monitoring your blood pressure helps you to maintain heart healthy habits.
High blood pressure is a risk factor for heart disease. Remember to take your blood pressure today.
Have you forgotten to take your blood pressure today?

Table 2: Clinician Messages

Clinician Adherence: A text or call was made to participants that did not fully adhere to the study requirements the week before.
Clinician B.P.: Clinicians made a text or call to participants if there was a deviation from typical participant blood pressure values.
Clinician Positive Reinforcement:A text or call was made to participants if they were adhering and had good levels of physical activity.

4.1 Quantifying Adherence

For physical activity, we consider the number of days a participant was active above a certain threshold (≥ 1000 points, which is equivalent to 21 minutes of moderate (4 MET) physical activity) [2]. We define an active day based on the 2008 Physical Activity Guidelines for Americans [15], which sets the minimum requirement of physical activity to 150 minutes, which is about 21 minutes daily. As a result we define an active day to be at-least 21 minutes of moderate activity. Since participants often missed a few days a week wearing the activity device daily, we could not measure accurately whether the participant truly performed 150 minutes of activity throughout the week, as a result we considered the number of active days in a week as a measure of adherence. The daily questionnaires acted as prompts, reminders and reinforcement of their education. Since participants could forget a day or two to answer the daily questions, we considered participants adherent in this category if they completed at-least 50% of the questions, which includes 3 out of the 6 daily questionnaires a week. Participants adhere in blood pressure if we receive at-least one blood pressure measurement a week. The weekly questionnaire was completed as a single unit once a week, as a result they were considered adherent if they completed all the questions in the weekly questionnaire.

4.2 Data Analysis

From the final dataset of the intervention group we removed 16 participants (8 completed baseline but did not return to the study, and 8 did not have enough reliable data for prediction). Overall, we end up with a dataset of 925 valid weekly datapoints totaling 25 weeks from 37 participants. We only use 25 instead of the 26 weeks, because we do not have a priori information to predict adherence in week one.

We first attempt to determine whether each type of automated or clinician message correlates with adherence or non-adherence to study protocols on a weekly basis. We then attempt to study, using machine learning algorithms, how well the data can help predict adherence in four categories: active days, daily questionnaire, weekly questionnaire, and blood pressure measurement.

4.2.1 Analyzing Correlation of Messages

Firstly, we would like to explore how clinician and automated messages correlate with the following week's adherence. We provide statistical tests of independence for each of the seven intervention types defined in Table 1 (4 automated messages and 3 clinician messages) and the adherence outcome of the four categories: daily questionnaire, weekly questionnaire, blood pressure measurements, and active days. In each category we split the weeks for each participant into those that adhered and those that did not adhere. We then compare the participants that received a clinician or automated message with those that do not, and analyze whether they remain adherent or not the following week. We do this by testing the hypothesis that the two distributions have equal means using a Welch t-test. The Welch test will give us an idea of whether interventions had a positive or negative impact on participant adherence, especially given unequal sample sizes (which is evident in our study). Due to the limited number of participants in this study, participants that did not adhere automatically received automated reminders, however in a larger future trial we will attempt to study the effects of micro-randomization of messages among participants.

4.2.2 Predicting Weekly Participant Adherence

We explore whether it is possible to predict weekly adherence using collected data from the previous week as well as baseline contextual information. Such a system is useful in optimizing clinician intervention and minimizing the associated costs by allowing clinicians to target the participants that most probably will not adhere and as a result need more support. We train predictive models for Active Days, Blood Pressure, Daily and Weekly Questionnaires. Our goal is to categorize patients into those that will adhere and those that will not for each category. We use the full dataset (925 datapoints) and combine weekly adherence features (seven categories of messages) with baseline contextual features to predict adherence levels the following week.

The predictive pipeline consists of feature selection using the information gain criterion [8] and four classification algorithms (Figure 2). We compare classification models using four well-known algorithms: C4.5, Random Forests, Bayesian Networks and Logistic Regression. For each of these classifiers, we select commonly used training parameters (default parameters in Weka) as fine-tuning the classifiers is beyond the scope of this paper.

5. RESULTS AND DISCUSSION

5.1 Analyzing Correlation of Messages

The results of the two-tailed t-tests (Welch) are shown in Table 3. We only show the statistically significant ($p < 0.01$) results that had a positive impact. The 95% percent confidence interval shows the difference in next week adherence mean values between the participants that received the intervention (*With*) and those that did not (*Without*). The difference will be negative (showing a positive effect) when those that did not receive the intervention have a lower mean than those that did.

Overall, clinician positive reinforcement texts and calls resulted in the most significant effect across all categories of adherence. For the Active Days category, those that did not adhere and received positive reinforcement had between 0.24 and 3.26 more active days the following week than those that did not receive positive reinforcement ($p = 0.0268$). Clinician positive reinforcement was also important in the Active Days category among those that adhered ($p = 0.00002$) in helping them maintain or improve their adherence level. Finally, positive reinforcement resulted in positive effects on blood pressure both in the non-adherent and adherent groups, and for daily and weekly questionnaires it helped among those that were not adherent.

For physical activity adherence, we further break down the participants into low, medium and high activity adherence levels ((0,2), [2,5], (5,7] days). In this case, we can see that the intervention impact for really low and really high adherence participants is inconclusive. However, clinician positive reinforcement is strongly correlated ($p = 0.0124$) with increased activity adherence for inconsistently adhering participants (those that exhibited anywhere between 2-5 active days) during the following week.

Table 3: Statistically significant interventions that result in different levels of adherence. Results are generated using two-tailed t-tests (Welch)

	t	p-value	95% confidence interval	Without	With
Active Days [did not adhere]					
Clinician Positive Reinf.	-2.5402	0.0268	(-3.2646,-0.2409)	389	12
Active Days [adhered]					
Daily Reminder	-1.9512	0.0538	(-1.1320,0.0093)	79	445
Inspirational Reminder	-3.3430	0.0081	(-3.5810,-0.7023)	10	514
Clinician Adh.	1.7689	0.0777	(-0.0398,0.7530)	344	180
Clinician Positive Reinf.	-4.5109	0.00002	(-1.6784,-0.6529)	453	71
Daily Questionnaires [did not adhere]					
Clinician Positive Reinf.	-4.9274	0.0003	(-7.7752,-3.0250)	308	13
Weekly Questionnaires [did not adhere]					
Inspirational Reminder	-14.0631	0	(-5.0586,-3.8171)	3	338
Weekly Reminder	-14.1000	0	(-5.1023,-3.8529)	6	335
Clinician Positive Reinf.	-1.8277	0.0873	(-6.3437,0.4836)	326	15
Blood Pressure [did not adhere]					
Clinician Positive Reinf.	-3.5535	0.0024	(-0.6586,-0.1685)	366	17
Blood Pressure [adhered]					
Clinician Positive Reinf.	-2.0323	0.0450	(-0.2096,-0.0024)	476	66

Table 4: Clinician Positive Reinforcement and Inconsistent Adherence

	t	p-value	95% confidence interval	Without	With
Did not adhere the previous week (<2 active days)	-1.7230	0.1346	(-3.8388,0.6569)	300	7
Adhered Inconsistenly (2-5 active days)	-2.7541	0.0124	(-2.2123,-0.3036)	280	18
Fully Adhered (>5 active days)	-0.4444	0.6579	(-0.7589,0.4816)	173	53

5.2 Predicting Weekly Participant Adherence

For each algorithm we used a Leave One Out Cross Validation (LOOCV) evaluation methodology. In this case, LOOCV refers to all the data points collected from the same participant. Accuracy, Area Under the Curve (AUC) and standard deviation of error across LOOCV for each classification task and each algorithm are compared in Figure 5.2. Figure 3 shows the receiver operating characteristic (ROC) curve for each classifier.

As seen in Figures 5.2 and 3, it is possible to predict participant adherence from one week to the next with an accuracy of 82.5%, 72.4%, 83.4%, 76.8% for Active Days, Blood Pressure, Daily and Weekly Questionnaires respectively.

The most predictive features selected from our pipeline are shown in Table 5. Since evaluation was done using LOOCV we report the features that were selected in the majority of the folds. Interestingly, the contextual feature that is most predictive is a participant's initial BMI and Lipid profiles. From the weekly data, the number of active days and number of daily questions answered are the most predictive features for a participant's adherence during the following week.

5.3 Discussion

In the Women's Heart Health Study based on a sample of young Black women (ages 25-45) in the urban Los Angeles setting staying connected via a smart phone application had a positive effect on adherence to an educational program and behavior change over a 6 month period. Overall, clinician positive reinforcement text messages and calls resulted in the most significant effect across all categories of adherence (BP, Daily Questionnaires, Weekly Questionnaires and Active Days). Recent studies have shown that case management and additional support given to patients by nurses, or other professional team members can impact patient's health [23]. In our group of women education and setting attainable individualized goals was of utmost priority given the presence of two or more CVD risk factors for CVD and/or stroke. We set out to explore the use of technology as an adjunct to previous findings on lifestyle and behavioral interventions that have not been sustainable. Instituting individualized health coaching, maintaining the connection and providing targeted support to meet these goals was successful in participants who were well motivated and consistent throughout the program. Of note, our findings show that RHMS messages were successful in motivating the group of participants that were inconsistently adhering to the study regimen one week, and in response to the communication improved their adherence or maintained positive adherence

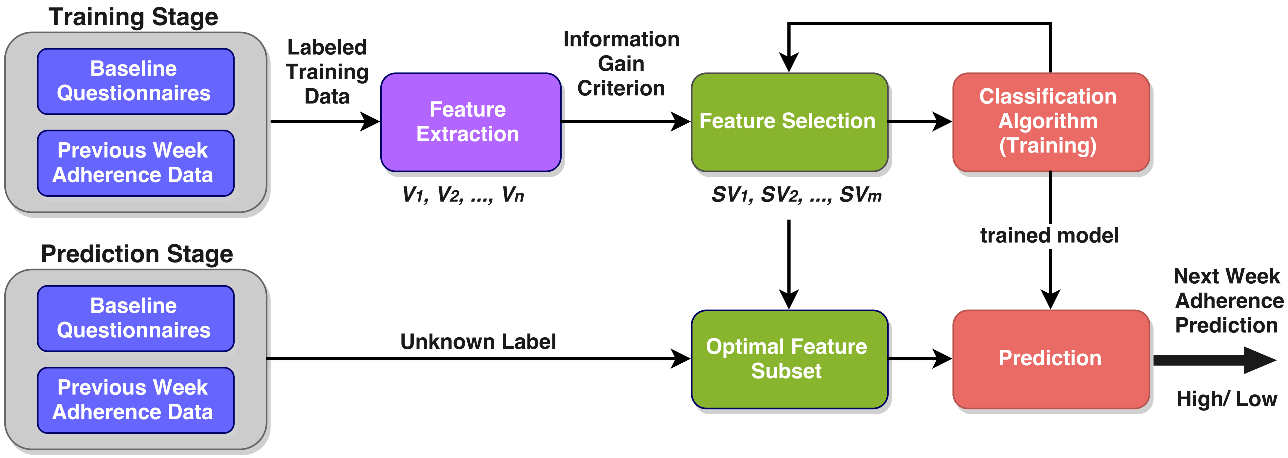

Figure 2: Predictive pipeline in Wanda-CVD to estimate participant adherence the following week.

Table 5: Most Predictive Features for Adherence

Active Days	
Active Days & Level	: Physical activity during the previous week that the participant adhered
Daily Quest. Adherence	: Number of daily questions answered the previous week (1-12)
BMI	: Body Mass Index of the participant the beginning of the study
HDL	: Lipid profile of the participant at the beginning of the study
Blood Pressure	
Daily Quest.	: Number of daily questions answered
Perceived Support	: Perception of help and support received from others (baseline)
WaistC	: Waist Circumferance of the at the beginning of the study
HDL	: Lipid profile of the participant at the beginning of the study
Daily Questionnaires	
Daily Quest. .	: Number of daily questions answered
Perceived Support	: Perception of help and support received from others
HDL / LDL	: Lipid profile of the participant at the beginning of the study
BMI	: Body Mass Index of the participant the beginning of the study
Weekly Questionnaires	
Daily Quest.	: Number of daily questions answered
Weekly Quest.	: Number of weekly questions answered
Blood Pressure Adherence	: Did the participant measure their blood pressure the previous week
HDL	: Lipid profile of the participant the previous week (1-12)

the following week. Additionally, results indicate that adherence during the previous week is the best predictor of adherence for the upcoming week.

6. CONCLUSION AND FUTURE WORK

In this era of M-Health, the Women's Heart Health Study has provided new knowledge and useful insights into the effectiveness of wireless coaching. In our study of urban young Black women the connection provided a relationship utilizing emotional support and motivation which appears to be very important among this group of women in making lifestyle and behavioral changes. In addition, in this group of women with CVD risk factors, clinician positive reinforcement resulted in significant improvements in participant adherence for participants that were not adhering well to the protocol. It further encourages participants who adhere to keep their levels of adherence increased. When exploring together the effects of interventions, we found that participants in the middle of the adherence spectrum benefited most from it. Finally, we presented a framework for predicting weekly participant adherence based on weekly and contextual features. Such a framework has the potential to optimize clinician intervention by informing them about participant future adherence. In the future we hope to further validate our pilot study findings in a larger sample in diverse settings applying a micro-randomized approach to health coaching. Interventions like these that take little time and resources may be a major factor in increasing prevention efforts and decreasing the incidence of chronic disease in minority populations.

7. ACKNOWLEDGMENTS

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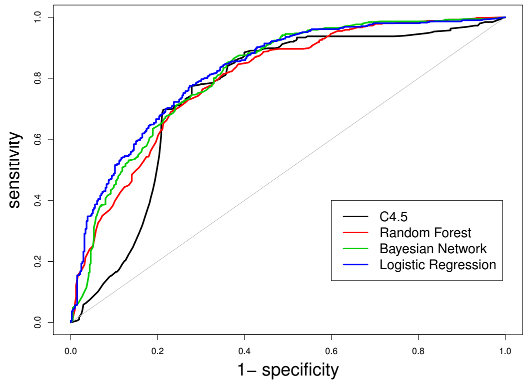
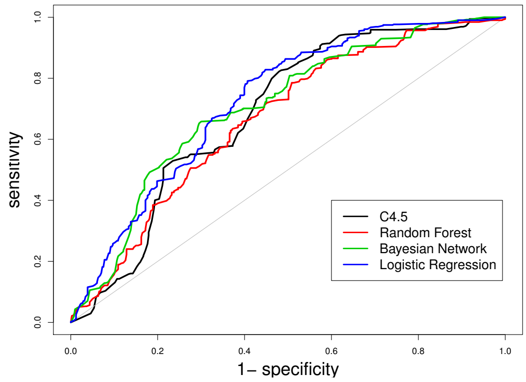
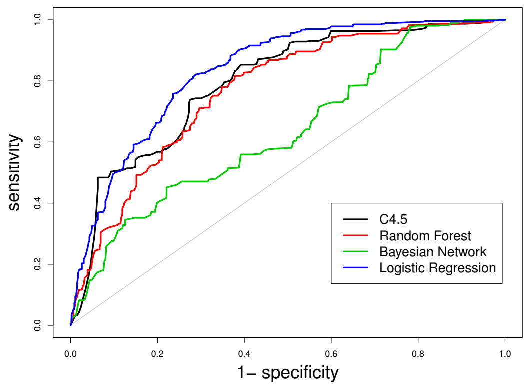
(a) Active Days



(b) Blood Pressure Adherence



(c) Daily Questionnaires



(d) Weekly Questionnaires

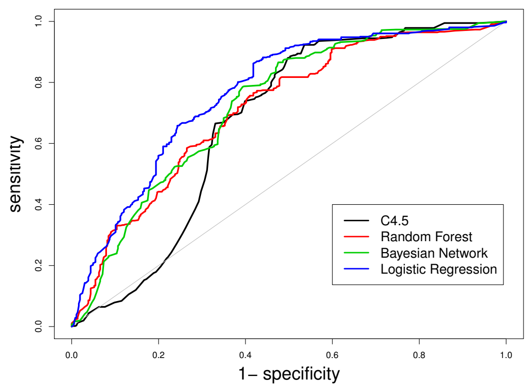
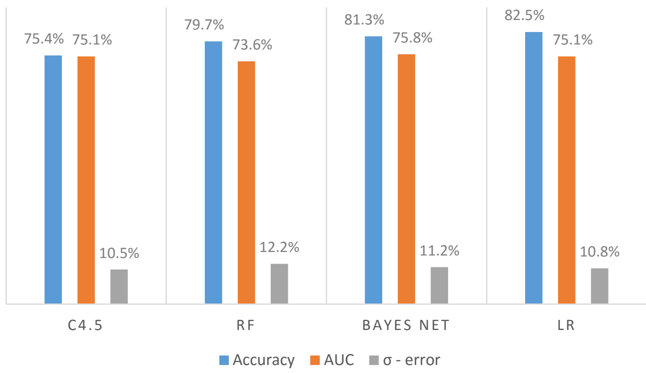
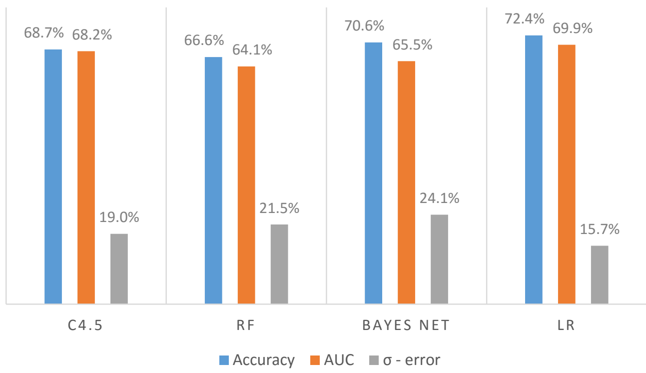


Figure 3: Receiver operating characteristic curves for each of the prediction tasks.

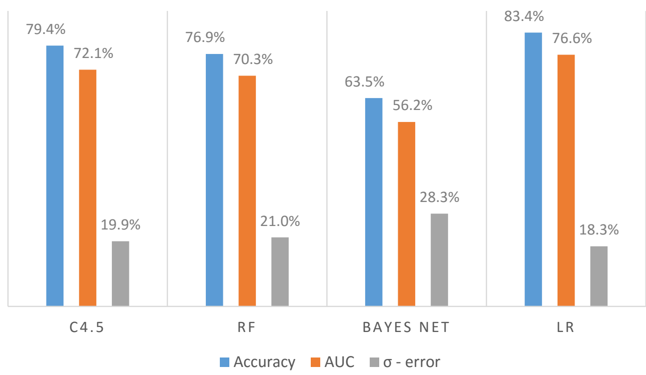
(a) Active Days



(b) Blood Pressure Adherence



(c) Daily Questionnaires



(d) Weekly Questionnaires

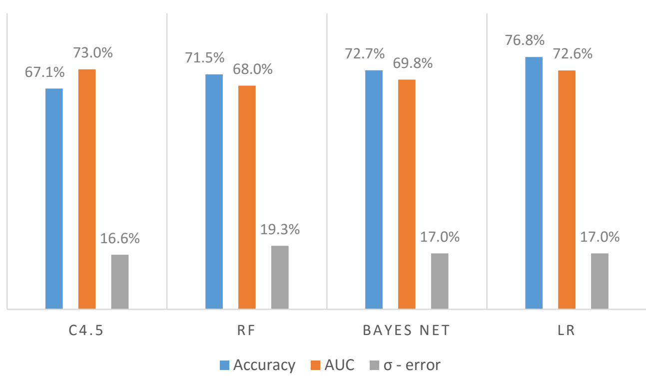


Figure 4: Accuracy, Area under the Curve and LOOCV standard deviation of error for each of the prediction tasks and each of the classifiers

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