A Framework for Predicting Adherence in Remote Health Monitoring Systems

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ABSTRACT

Remote health monitoring (RHM) systems have shown potential effectiveness in disease management and prevention. In several studies RHM systems have been shown to reduce risk factors for cardiovascular disease (CVD) for a subset of the study participants. However, many RHM study participants fail to adhere to the prescribed study protocol or end up dropping from the study prior to its completion. In a recent Women's Heart Health study of 90 individuals in the community, we developed Wanda-CVD, an enhancement to our previous RHM system. Wanda-CVD is a smartphone-based RHM system designed to assist participants to reduce identified CVD risk factors by motivating participants through wireless coaching using feedback and prompts as social support. Many participants adhered to the study protocol, however, many did not completely adhere, and some even dropped prior to study completion. In this paper, we present a framework for analyzing baseline features to predict adherence to prescribed medical protocols that can be applied to other RHM systems. Such a prediction tool can aid study coordinators and clinicians in identifying participants who will need further study support, leading potentially to participants deriving maximal benefit from the RHM system, potentially saving healthcare costs, clinician and participant time and resources. We analyze key contextual features that predict with an accuracy of 85.2% which participants are more likely to adhere to the study protocol. Results from the Women's Heart Health study demonstrate that factors such as perceived health threat of heart disease, and perceived social support are among the factors that aid in predicting patient RHM protocol adherence in a group of African American women ages 25-45.

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1. INTRODUCTION

Despite recent advances in technological and pharmacological therapies, CVD remains the leading cause of death for both men and women [1]. However lifestyle changes to healthy eating, exercise and the adoption of self-management skills can greatly prevent or reduce the progression of CVD. Remote health monitoring (RHM) systems are increasingly being adopted for the purpose of disease prevention. However, studies on the efficacy of RHM systems continue to produce controversial results, some studies report the benefits of RHM [7, 16], while others center on RHM failures [9]. Desai explains that it is likely that no single approach to health monitoring will be effective, rather more patient personalization in RHM systems is necessary [9]. To be able to design systems that are more personalized, we propose a method to predict, based on contextual features, which individuals would be more likely to adhere to a particular RHM protocol.

Our goal in predicting RHM adherence is to identify which patients will adhere to prescribed medical regimens, and which individuals will require further customization in a RHM system. Such a tool can aid clinicians in identifying participants more likely to capitalize on the technology provided, while at the same time identifying participants that might need further support.

In this paper, we describe an enhanced RHM system named Wanda-CVD that is smartphone-based and designed to provide wireless coaching and social support to participants. In a six month study designed to reduce CVD risk factors in young black women, Wanda-CVD was deployed to about half (53) of the total study population (90). CVD prevention measures are recognized as a critical target by health care organizations worldwide i.e. the World Health Organization, the Institute of Medicine and a primary goal for Healthy People 2020 [10].

Given the expense of purchasing smartphones and their resultant data/service plans, we were motivated to identify rationale for the successes and failures regarding participant adherence to the study protocol. Several of the participants in the Women's Heart Health study adhered to the medical protocol, however like many other longitudinal studies several participants did not adhere to the study protocol as outlined in the signed informed consent. Based on this pilot study, we were interested in identifying a method to predict adherence to the protocol using contextual-based features measured at baseline. The purpose of this work will not only help us better understand which people adhere to RHM systems, but also create a minimal subset of questions to screen potential participants prior to enrolling them into a RHM study or system. This could save time and resources but also help us learn how to mold our current health monitoring systems to better suit different populations. Because dropout rates increase with questionnaire length, developing such a prediction model could also aid in reducing the burden of participants by identifying important questions that relate to the adherence and success criteria of a study [20].

This paper is organized as follows. Section 2 describes the related work. Section 3 presents the Wanda-CVD system and the Women's Heart Health study in which it was tested. Section 4 describes the baseline questionnaires used in the study and the key contextual features used in prediction. Section 5 provides a definition of user adherence to the prescribed medical protocol. Section 6 discusses the machine learning framework used to predict RHM adherence. Section 7 presents the results on the essential features selected by our framework and the accuracy of each predictive model. Section 8 provides a discussion of the results. Finally, we conclude in Section 9.

2. RELATED WORK

According to Bui et al., the potential for RHM systems to improve the management of heart failure patients is substantial [7]. Chaudhry et al. shows a high correlation between increases in body weight and hospitalization for heart failure beginning at least 1 week before hospital admission [8]. However, Koehler et al. shows that compared to usual care, remote health monitoring had no significant effect on all-cause mortality or on cardiovascular death or HF hospitalization [15]. Desai also argues that home monitoring for heart failure does not necessarily improve patient readmission rates and outcomes [9].

Despite the increasing research in RHM systems, it remains to be seen whether the technical feasibility and effectiveness of such systems can generate optimal patient outcomes and prevent chronic disease in a cost effective manner [19]. In order to better assess who benefits from a RHM system, we must first be able to see which individuals are most likely to adhere to RHM systems.

Chronic conditions have been perceived as a unique market for the use of smartphone applications [25]. A recent review of over 60 studies found chronic conditions such as diabetes mellitus and cardiovascular disease have in particular always been perceived as a special 'niche market' for smartphone apps [21]. Krishna et al. found significant improvements in compliance to medical regimens using cell phones and text messaging interventions [17]. However, while smartphones are found to be useful in a RHM system, we analyzed whether this guarantees adherence to a RHM system.

Several RHM studies report patient characteristics of participants that succeeded. In this paper we attempt to identify key contextual features that help predict participant adherence to physical activity, daily questionnaires and blood pressure measurements in a smartphone-based RHM system. In a previous effort we attempted to predict outcome success based on contextual-features [4]. In reviewing current literature, we find extensive research regarding adherence to medication prescription [13], however, we believe this is the first work in predicting adherence to RHM systems.

3. REMOTE HEALTH MONITORING SYSTEM

3.1 Wanda-CVD

This RHM system is an advanced version of a previous RHM system we developed named Wanda [18] that targets patients at risk of CVD through Wireless Coaching. Wireless Coaching is in the form of automated messages prompting the user to take certain actions, such as measuring their blood pressure or reminding them to increase exercise intensity. There are several key components in the complete design of the Wanda-CVD system illustrated in Figure ??. The first component is the Android-based smartphone application designed as a means to collect data from the user, while displaying clinician feedback to the user. 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 then transmits this information to a backend server, where it is stored and machine learning algorithms process the data to identify patterns and learn patient models. The server provides a graphical user interface in the form of both a web- and tablet-based portal to the nurses to provide a visual cue and summary of what is happening with each patient, alerting them when a matter requires their attention [5, 3, 2].

3.2 Women's Heart Health study

Our system has been deployed in the Women's Heart Health Study, which 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. It attempts to analyze the effects and lifestyle changes that result from social support via automated Wireless Coaching. In this study 53 participants in the intervention group completed baseline screening. They received nutrition and lifestyle education, along with a Bluetooth blood pressure monitor and a smartphone to be worn around the waist to detect physical activity. The control group received usual care which included identification of CVD risk factors. The system transmits participant measured data in real-time using Wi-Fi and 3G/4G technology. The intervention group received four educational classes focused on self-management of diet, nutrition, physical activity and stress reduction. After completion of baseline screening of cholesterol levels, blood pressure, BMI, and demographic and psychosocial questionnaires and completion of the educational classes, the participants were taught how to wear and manage the phones and blood pressure monitors. They were told that the primary purpose of the smartphone was to track their physical activity while providing a user interface and a mechanism for automated feedback. The subjects were able to send/receive unlimited text messages along with unlimited data plans.

4. BASELINE CONTEXTUAL FEATURES

During the face to face baseline, 3 and 6 months visits, physiological as well as psychological outcomes are measured via anthropometric measures, questionnaires and a software program. The focus of this report is to predict what contextual data from baseline questionnaires can help us indicate which subjects adhere in a RHM system. This type of information can guide us in improving our understanding of potential motivators that can enhance RHM systems while saving time and resources. At baseline we collect several clinical measures, demographic information, and questionnaires. Table 1 lists the different categories, most in the form of questionnaires provided to the participants at baseline. The questionnaires are grouped into categories such as: family history (FAMHX), anxiety (BRIEFS), depressive symptoms (PHQ), quality of life (SF), stress levels (STRESS), perceived threat of heart disease (PMT), and available social support group (SOCSUP). We also incorporate the following demographic information as features: age, education level, financial status, social status, employment status, and literacy. Our goal is to identify a subset of the measurements and questions that determine participant CVD study adherence.

Table 1: Baseline measurements and questionnaires

Acronym	Measurements	Purpose
	Clinical Measures	Waist, BMI, BP, Lipids
FAMHX	Demographics-Health History	Family & Medical
BRIEFS	Brief Symptom Inventory	Anxiety
PHQ	Patient Health Questionnaire	Depressive Symptoms
MOSSAS	Medical Outcomes Study-SAS	Adherence
SF	MOS-SF-12	Quality of Life
PMT	Protection Motivation Theory	Health threat of heart disease self efficacy
STRESS	INTERHEART STRESS	Stress
SOCSUP	Perceived Social Support Scale	Social Support

5. ADHERENCE

In order to quantify the feasibility of our system, we defined a metric of adherence in coordination with our nurses and medical experts. We provide an overall adherence rate, as well as a per category adherence rate. There are currently three categories each requiring feedback from the participant: daily questionnaire (DQ), blood pressure (BP) measurement, and physical activity (Activity). We add a fourth category which is the average of the three categories (Overall). We determine adherence on a weekly basis for each category c. The daily questionnaire acted as prompts, reminders and reinforcement of their education, we considered participants adherent in DQ if they completed at-least 50% of the questions, which includes 3 out of the 6 daily questionnaires a week. Participants adhere in BP if they we received 50%, or at-least one measurement of BP a week (they were asked to measure their BP twice in one sitting, a week). Activity adherence is defined as participants exerting at-least 150 minutes of moderate intensity activity per week, based on the 2008 Physical Activity Guidelines for Americans [14]. We define adherence for each subject s and category c in week i by:

$$A(i)_s^c = \begin{cases} 1 & \text{if } s \text{ adhered in week } i \text{ in category } c \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

The adherence for n weeks is:

$$A_s^c = \frac{\sum_{i=1}^{n} A(i)_s^c}{n}. \tag{2}$$

An overall adherence rate, $A_s^{Overall}$, is calculated which is an average of the adherence A_s^c across each of the three categories. Also, a label for each subject and category L_s^c is set to 1, if they adhered, and 0 otherwise. Adherence is set at 70% for each category:

$$L_s^c = \begin{cases} 1 & \text{if } A_s^c > 70\% \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

There is currently no consensus on how to best define adherence. According to the literature, medication-based adherence research defines patients to be adherent if there medications are available 80% of the time [13]. According to the Center for Medicaid and Medicare Services (CMS), adherence is defined as use of the CPAP device at-least 70% of the time [22]. We accordingly set the adherence to the RHM system to be 70%.

6. PREDICTING ADHERENCE

The conventional feature selection algorithms usually focus on specific metrics to quantify the relevance and/or redundancy to find the smallest subset of features that provides the maximum amount of useful information for prediction. Thus, the main goal of feature selection algorithms is to eliminate redundant or irrelevant features in a given feature set. Applying an effective feature selection algorithm not only decreases the computational complexity of the system by reducing the dimensionality and eliminating the redundancy, but also increases the performance of the classifier by deleting irrelevant and confusing information.

The two well-known feature selection categories are the filter and wrapper methods. Filter methods use a specific metric to score each individual feature (or a subset of features together), and are usually fast and much less computationally intensive. Wrapper methods usually utilize a classifier to evaluate feature subsets in an iterative manner according to their predictive power [11]. We applied the wrapper method, testing on multiple combinations of feature subsets and classifiers including: kNN, BayesNet, and Random Forest. The optimal feature subset and classifier combination is selected. kNN classifier is defined by a majority vote of its neighbors, with the object being assigned

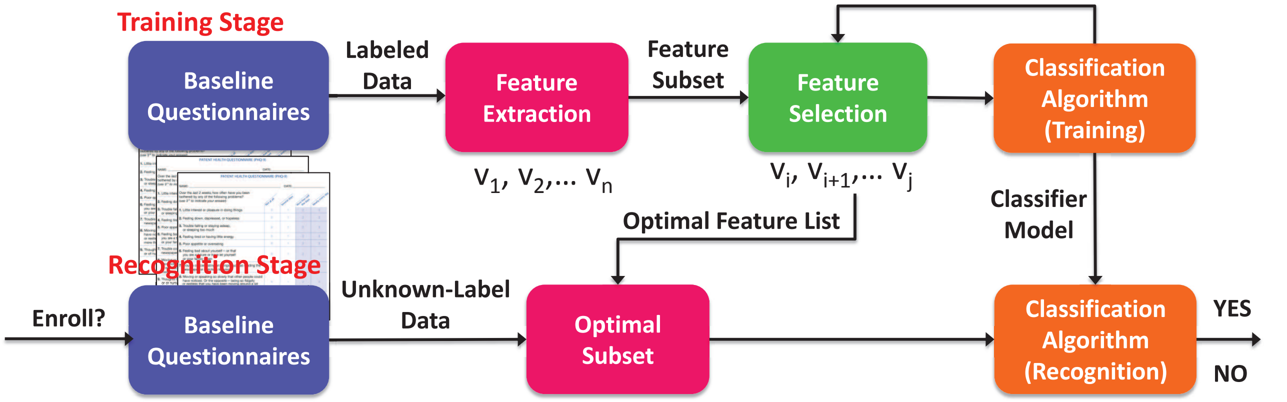


Figure 1: Wanda-CVD Prediction Methodology

to the label of the majority of its k nearest neighbors [6]. A Bayesian Network is a statistical model that represents a set of random variables (in our case each feature or baseline question), and their conditional probabilities using a directed acyclic graph (DAG) [23]. Random Forests is an ensemble learning classification method comprising a collection of decision tree predictors operating based on independent identically distributed random vectors. In this process, each tree casts a unit vote for the most popular class [24]. Figure 1 provides an illustration of the prediction framework, where an optimal feature subset and classifier is trained based on baseline measurements and questionnaires to distinguish between participants that adhered to the prescribed medical regimen.

The classifier then assigns a probability to each data sample. We then adjust cut-off thresholds on the probability to generate labels for each sample, and generate false positive rates and true positive rates for each cut-off point. We then generate Receiver Operating Characteristic (ROC) curves to evaluate the performance of each classifier under Leave-one-subject-out Cross Validation (LOSO CV). The area under the curve (AUC) is then used to measure the discrimination, or the ability of the classifier to correctly classify RHM participant adherence for each outcome category.

7. RESULTS

7.1 Population

According to our definition of adherence, 52.8% of the participants adhered to the overall prescribed medical regimens, which provides a balance in the number of participants in each category. Table 2 shows the adherence results for each of the categories.

Table 2: Subject Adherence (Total Participants: 53)

Category (c)	Adherence (%)	Adhered	Not Adhered
Overall	52.8%	28	25
Activity	47.2%	25	28
DQ	49.1%	26	27
BP	58.5%	31	22

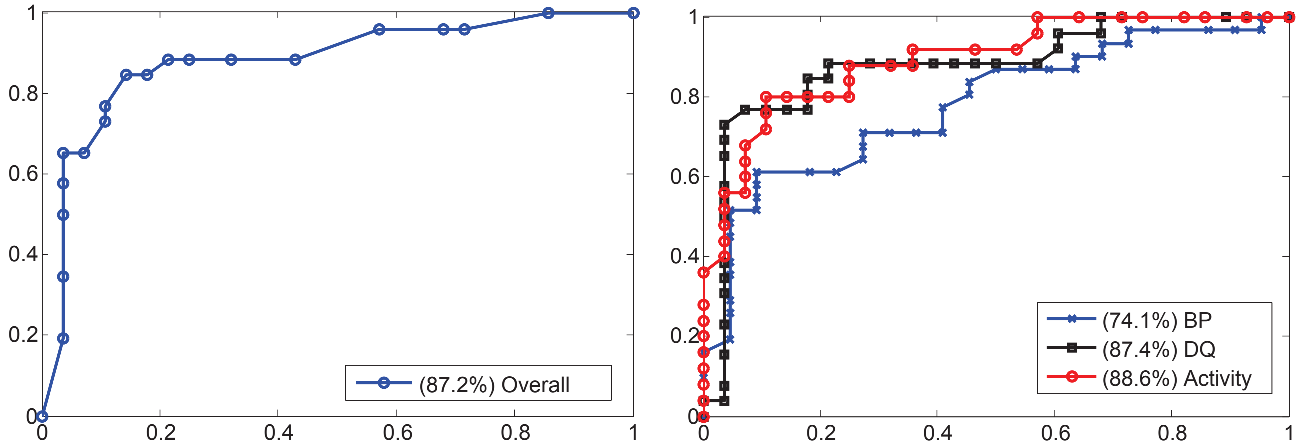
7.2 Overall

Figure 2a provides ROC curves for prediction of the Overall category. The accuracy and AUC for the Overall category using Random Forest with 100 trees is 85.2% and 87.2% respectively. The accuracy for predicting Activity, DQ and BP is 81.1%, 83.3%, and 73.6%. Figure 2b provides ROC curves for prediction of Activity, DQ and BP, resulting in a 88.6%, 87.4%, and 74.1% AUC, respectively. Predicting BP adherence was the most challenging. The remainder of this section discusses the features selected for each predictor.

According to our results, the Random Forest classifier with 100 trees was selected to best predict Overall adherence. The optimal feature selection algorithm chosen was the Correlation based Feature Subset (CFS) selection which determines the worth of each subset of attributes by calculating the predictive power of each feature along with its degree of redundancy [12]. Features that were highly correlated with the class, but have low inter-correlation are chosen. Six features were selected to predict Overall adherence. They include participant baseline hsCRP values, triglycerides, infant gestational diabetes, income level, and responses to two questions from the PMT questionnaire. The following were the chosen features:

1. CRP: Baseline CRP measurements.
2. PMT15: (Thoughts about your health) The thought that I might get heart disease in the future scares me.
3. PMT19: (Thoughts about your health) Regular physical exercise will not keep me from having heart disease in the future.
4. TG: Baseline triglyceride measurements.
5. PREGDM: Reproductive history: Infant gestational diabetes.
6. INCOM: Considering the amount of money that comes into the household for you to live on, would you say you: OPTION-1) Are comfortable, have more than enough to make ends meet. OPTION-2) Have enough to make ends meet. OPTION-3) Do not have enough to make ends meet.

Table 3 describes each feature selected, the range of responses and response statistics in the dataset that support the inclusion of each feature.



(a) Overall ROC curve

(b) Activity, DQ and BP ROC curve

Figure 2: ROC curves with corresponding AUC to measure performance of each predictor corresponding to each of the following categories: Overall, Physical Activity (Activity), Daily Questionnaire (DQ), and Blood Pressure (BP).

Table 3: Subject Overall Adherence

Measurement	Range of Responses	Reasoning
Baseline CRP	0.3mg/L - >10mg/L	87.5% of participants with levels of hsCRP > 3.0mg/L did not adhere to the protocol (24 had values > 3.0mg/L).
PMT15	Strongly (Agree - Disagree)	All the participants that were inclined to disagree adhered to the study protocol (6 were likely to (Strongly) Disagree).
PMT19	Strongly (Agree - Disagree)	All the participants that strongly agreed adhered to the protocol (5 were likely to Strongly Agree).
TG	<45 - 512mg/dL	84.6% of participants with TG > 100mg/dL did not adhere to the protocol (13 had values > 100).
PREGDM	Yes or No	All 3 women that had infant gestational diabetes did not adhere to the protocol.
INCOM	OPTION 1 - 3	91% of the subjects that were comfortable (OPTION 1) did not adhere to the protocol.

7.3 Physical Activity

We were able to predict adherence to physical activity with 81.1% accuracy and a ROC AUC of 88.6% (See Figure 2b). Our framework selected the Random Forest classifier with 10 trees as well as the Correlation-based Feature Subset (CFS) selection algorithm to predict physical activity adherence. Eight features were selected to predict Activity adherence. They include participant baseline hsCRP values, triglycerides, responses to three questions from the PMT questionnaire, responses to two questions from the SOCSUP questionnaire, and one question from the PHQ questionnaire. The following were the selected features:

1. CRP: Baseline CRP measurements.
2. TG: Baseline triglyceride measurements.
3. PMT15: (Thoughts about your health) The thought that I might get heart disease in the future scares me.
4. SOCSUP11: My family is willing to help me make decisions.
5. SOCSUP3: My family really tries to help me.
6. PMT19: (Thoughts about your health) Regular physical exercise will not keep me from having heart disease in the future.
7. PMT17: (Thoughts about your health) If I eat more fruits and vegetables, my risk for developing heart disease in teh future will be less.
8. PHQ2: Feeling down, depressed or hopeless.

Table 4 describes each feature selected, the range of responses and response statistics in the dataset that support the inclusion of each feature.

7.4 Questionnaire

We were able to predict adherence to daily questionnaires (DQ) with 83.3% accuracy and a ROC AUC of 87.4% (See Figure 2b). Our framework selected the Random Forest classifier with 100 trees as well as the Correlation-based Feature

Table 4: Subject Activity Adherence

Measurement	Range of Responses	Reasoning
CRP	0.3mg/L - >10mg/L	87.5% of participants with levels of hsCRP > 3.0mg/L (24) did not adhere to the protocol.
TG	<45 - 512mg/dL	84.6% of participants with TG > 100mg/dL did not adhere to the protocol (13 had values > 100).
PMT15	Strongly (Agree - Disagree)	All the participants that were inclined to disagree adhered to the study protocol (6 were likely to (Strongly) Disagree).
SOCSUP11	Very Strongly (Disagree - Agree)	80% of participants (10) that were inclined to disagree adhered to the protocol.
SOCSUP3	Very Strongly (Disagree - Agree)	All (5) participants that were inclined to disagree adhered to the protocol.
PMT19	Strongly (Agree - Disagree)	All the participants that strongly agreed adhered to the protocol (5 were likely to Strongly Agree).
PMT17	Strongly (Agree - Disagree)	No one disagreed with this statement. But all (5) women that somewhat agreed (not completely agreed) adhered to the protocol.
PHQ2	Not at all - Nearly every day	No one said nearly every day. But all (4) the women that responded with "More than half the days" did not adhere to the protocol.
INCOM	OPTION 1 - 3	91% of the subjects that were comfortable (OPTION 1) did not adhere to the protocol.

Subset (CFS) selection algorithm to predict questionnaire adherence. Five features were selected to predict DQ adherence. They are similar to those selected to predict Overall adherence, which suggests a potential link between daily questionnaire adherence and overall study adherence. The following were the selected features:

1. CRP: Baseline CRP measurements.
2. PMT15: (Thoughts about your health) The thought that I might get heart disease in the future scares me.
3. PMT19: (Thoughts about your health) Regular physical exercise will not keep me from having heart disease in the future.
4. TG: Baseline triglyceride measurements.
5. INCOM: Considering the amount of money that comes into the household for you to live on, would you say you: 1) Are comfortable, have more than enough to make ends meet, 2) Have enough to make ends meet, 3) Do not have enough to make ends meet.

7.5 Blood Pressure

We were able to predict adherence to blood pressure with 73.6% accuracy and a ROC AUC of 74.1% (See Figure 2b). Our framework selected the Random Forest classifier with 10 trees as well as the Correlation-based Feature Subset (CFS) selection algorithm to predict blood pressure adherence. Seven features were selected to predict BP adherence. The following were the selected features:

1. EMPTSTAT: Employment status. 1) Employed full or part time outside the home, 2) Unemployed by choice, 3) On sick leave or disability, 4) A homemaker, 5) Retired, due to illness, 6) Retired, not due to illness, 7) Unemployed, laid off.
2. HR: Baseline measured resting heart rate.
3. SLFTEST4: I am able to do things as well as most people.
4. SF7: During the past 4 weeks, how much of the time has your physical health or emotional problems interfered with your social activities (like visiting friends, relatives, etc.).
5. WT: Baseline weight measurement (in pounds).
6. CRP: Baseline CRP measurement.
7. BP: Baseline Systolic BP measurement.

Table 5 describes each feature selected, the range of responses and response statistics in the dataset that support the inclusion of each feature.

8. DISCUSSION

Innovative designs for RHMS are rapidly becoming appealing as an innovative and cost effective method of instituting behavior change, increasing adherence to medication regimens or decreasing repeat hospitalizations through early symptom recognition in chronic disease. In all of these circumstances it is the goal to engage the individual as a partner in preventing or managing a chronic disease. Inherently the research and development fees upfront are very costly. Whether it is a study for the development of technology or the actual implementation of a monitoring system the monetary investment is considerable. When an innovative piece of technology is developed it is easy to recruit individuals who believe that this "will do it for them" and engage in the activity without thinking about the commitment involved.

The Theory of Reasoned Action was used as the overarching theory for the Women's Heart Health Study. Given the educational component and the social support afforded to the women who needed to change behavior the program looked appealing. It is no surprise that people that need treatment the most are often reluctant to capitalize on the

Table 5: Subject Blood Pressure Adherence

Measurement	Range of Responses	Reasoning
EMPSTAT	OPTION 1 - 7	All (3) participants that were unemployed or laid off did not adhere to the protocol.
HR	53 - 102 (beats/min)	Those with resting heart rates below 70 (7) and above 90 (3) did adhere to the protocol.
SLFEST4	Strongly (Agree - Disagree)	All the participants that Strongly Disagreed (3) did not adhere to the study protocol.
SF7	All the time - None of the time	All (6) participants that said All of the time adhered to the protocol.
WT	120 - 325 (lbs)	67% of women above 250 pounds (9) adhered to the protocol.
CRP	0.3mg/L - >10mg/L	72% of participants with levels of hsCRP > 5.0mg/L (7) adhered to the protocol.
BPS	92 - 170	44% of participants with systolic blood pressure > 140 did adhere to the protocol.

opportunity to receive it. Based on the results of the current study we found this to be true. Participants with an hsCRP greater than 3.0mg/L are often defined to be high risk for CVD. Based on our results 87.5% of this group did not adhere to all aspects of the study (See Table 3). Although as is evident in the adherence to blood pressure (See Table 5), the majority of the ladies having elevated hsCRP consistently took their weekly blood pressures. Also participants with high triglycerides weakly complied with multiple aspects of the study. More specifically the two participants with the highest values of triglycerides at baseline (512 and 650mg/dL) were the worst offenders.

As previously discussed, a battery of psychosocial tools were administered. It is interesting to note the that participants that were not afraid of the thought that they might get heart disease in the future (PMT15), and those that strongly agreed that regular exercise will not keep them from having heart disease (PMT19) adhered to participant protocols. An assumption made by study personnel is that adherence to such measures could potentially be attributed to the educational program CVD risk factors and self-management skills they received at baseline.

Contrary to our beliefs, it was surprising to find that individuals that could afford a comfortable living 91% (n=10 out of 11) of the subjects did not adhere to the study protocol. The likelihood that there were two working adults in the family and dining out may be more commonplace for families such as these could possibly explain this finding. The educational program stressed preparing fresh meals at home where you can control ingredients like fat content and sodium.

People who were more independent as evidenced by responses to SOCSUP11 and SOCSUP3 in Table 4 were more inclined to engage and adhere to increased physical activity which could mean that they utilized the education in self-management skills effectively.

9. CONCLUSIONS

Instituting RHM systems as a means of monitoring patients adherence to treatment regimens, identifying dangerous symptoms to wave off untoward clinical events or coaching individuals to change behavior to adopt healthier lifestyles is the wave of the future. Testing and applying this technology and resources is costly. With the emphasis on cost consciousness and cost efficiency in mind we are reporting a pilot study presenting a possibly useful framework for analyzing individual's baseline features or questionnaire responses to predict their level of adherence to prescribed medical protocols and the use of RHM systems. Such a prediction tool could potentially save costs including equipment, clinician and participant time and resources, while helping study coordinators and clinicians recruit participants to RHM systems. Identifying non-adherent groups can also aid in refining RHM systems to target such groups.

Our enhanced Wanda-CVD RHM system was tested in a Women's Heart Health study in a group of African American women ages 25-45. We analyze key contextual features that predict with an accuracy of 85.2% and a ROC AUC of 87.2% which participants are more likely to adhere to the study protocol. We are also able to predict adherence to physical activity, daily questionnaires and weekly blood pressure measurements with accuracy of 81.1%, 83.3%, and 73.6%, respectively. Further study in larger groups is warranted using similar analysis to identify groups who could benefit from RHM systems.

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