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Predicting Adherence to Use of Remote Health Monitoring Systems in a Cohort of Patients with Chronic Heart Failure

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Abstract

Background—It is unclear whether subgroups of patients may benefit from remote monitoring systems (RMS) and what user characteristics and contextual factors determine effective use of RMS in patients with heart failure (HF).

Objective—The study was conducted to determine whether certain user characteristics (i.e. personal and clinical variables) predict use of RMS using advanced machine learning software algorithms in patients with HF.

Methods—This pilot study was a single-arm experimental study with a pre- (baseline) and post- (3 months) design; data from the baseline measures were used for the current data analyses. Sixteen patients provided consent; only 7 patients (mean age 65.8±6.1, range 58–83) accessed the RMS and transmitted daily data (e.g. weight, blood pressure) as instructed during the 12 week study duration.

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Results—Baseline demographic and clinical characteristics of users and non-users were comparable for a majority of factors. However, users were more likely to have no HF specialty based care or an automatic internal cardioverter defibrillator. The precision accuracy of decision tree, multilayer perceptron (MLP) and k-Nearest Neighbor (k-NN) classifiers for predicting access to RMS was 87.5%, 90.3%, and 94.5% respectively.

Conclusion—Our preliminary data show that a small set of baseline attributes is sufficient to predict subgroups of patients who had a higher likelihood of using RMS. While our findings shed light on potential end-users more likely to benefit from RMS-based interventions, additional research in a larger sample is warranted to explicate the impact of user characteristics on actual use of these technologies.

Keywords

E-health; Telecardiology; Telehealth

Introduction

As remote monitoring systems (RMS) provide many opportunities for interactivity, they are particularly suited for implementing interventions that enhance patient activation, self-care, and quality of life by offering immediate feedback and advice to users [1]. Ample research show that RMS that integrate monitoring of vital signs (heart rate, systolic and diastolic blood pressure, weight, lower leg edema, etc.) and physiological measures (depression, anxiety, and quality of life, etc.), while analyzing, communicating and presenting data so that individuals are engaged and empowered in their own healthcare to enhance clinical outcomes for older adults [2]. Despite these promising prospects, actual exposure to RMS interventions is not living up to the high expectations, as only a limited proportion of older adults actually use these programs [3]. Furthermore, adherence to use of technology is a major barrier in wide-spread utilization of RMS. For example, 45% non-adherence rates are seen in use of RMS in patients with chronic heart failure (HF); in other words, only 55% used RMS devices at least 3 times a week based on five clinical studies involving patients with HF [2].

To increase adoption rates of RMS interventions, it is imperative to obtain detailed profiles of those who successfully adopt an intervention. It is important to gain more insight into characteristics of people who are being reached by the program, but also of people who are left unexposed to the program. These insights can be used to improve exposure to the program.[3] In addition, research that describes how functional requirements (evidence-based recommendations in clinical guidelines) and the functionality available in current RMS are congruent, are warranted to developing RMS interventions for older adults with chronic HF. Thus, the overall goal of this single cohort study is to distinguish between users (i.e. adherers) and non-users (i.e. non-adherers) of RMS using advanced machine learning software algorithms in a cohort of patients with HF. Specifically, we aimed to determine whether certain user characteristics (i.e. personal and clinical variables) predict use of RMS using context-aware prediction algorithms [4]. This study identifies the subgroups in HF population that are more likely to adhere to RMS. This would help researchers in the area of remote health monitoring systems for heart-failure to more efficiently recruit adherent users in order to evaluate their RMS design with respect to other aspects of RMS; In addition, we determine significant factors contributing to non-adherence of RMS in HF. One major benefit of acquiring such information is to help designing strategies to eliminate or reduce the impact of negative features in adherence to RMS or devising compensatory design strategies for the next generation RMS. The information ultimately directs researchers to boost the compliance to RMS in future.

Methods

This pilot study was a single-arm experimental study with a pre- (baseline) and post- (3 months) test design that was conducted between November 2009 and October 2010. Institutional Review Board approval was obtained prior to the start of the study. A total of 16 patients (mean age 65.8 ± 6.1, range 58–83) provided consent.

We used a RMS platform (i.e. WANDA-B)[5] developed by our team to collect daily weight, blood pressure (systolic & diastolic), heart rate, and responses to a symptom assessment survey. The system consists of a smartphone-based data collection gateway, an Internet-scale data storage and search system, and a backend analytics engine for diagnostic and prognostic purposes. A detailed description of WANDA-B is described elsewhere [6]. The purpose of WANDA-B is to capture symptoms that are difficult for a patient to report and changes in condition that evolve slowly over time. These improvements in turn, could enhance earlier detection of changes that may interfere with healthy and independent living.

For the current paper, we utilized baseline and follow-up data which included 200 features from each patient. Examples of such features include demographics, comorbidity, weight, psychosocial attributes (depression, anxiety, and quality of life), gender, age, marital status, ethnicity, education, employment status, and smoking and drinking history.

Data Analyses: Machine Learning Based Prediction Algorithms

We develop three machine learning software algorithms that use the collected data for predicting adherence to RMS. These software algorithms include Decision Tree (DT), Multi-Layer Perceptron (MLP), and k-Nearest Neighbor (k-NN) classifiers.

Decision tree builds classification models in the form of a tree structure. In fact, decision tree breaks down the dataset into smaller subsets recursively while at the same time an associated decision tree is incrementally developed [4]. The final result is a tree with decision nodes and leaf nodes. A decision node (a baseline attribute) may contain two or more branches. For example, a node that represent patient's age may have three branches for age < 50, ≥ 50 to < 75, and age ≥ 75. A leaf node (adherence and non-adherence in our application) represents a classification or decision. The topmost node in the tree which is associated with the best predictor is called root. An advantage of developing a prediction algorithm based on decision tree classification model is that the decision tree would automatically exclude non-prominent features from consideration for prediction purposes and would explicitly provide us with a list of prominent features. This is particularly important in our application where the number of baseline features is large. As our results show, however, only a very small number of features predicted adherence. Essentially these features are those that are used to construct the decision tree. Another advantage of decision tree based classification is that decision trees represent rules, which can be understood by humans and used for decision making.

We built our decision tree based on ID3 (Iterative Dichotomiser 3) algorithm.[4] Our approach involved a top-down greedy search through the space of possible branches that a feature can make without backtracking to the higher levels of the tree. Constructing branches at each node is based on the measure of entropy[7] and information gain [8]. The decision tree construction process starts from a root node and partitions the data into smaller subsets that contain data items with similar data types. In order to calculate similarity of a sample (i.e. data instance), entropy is used. Entropy is a measure of homogeneity of the set of samples (e.g. baseline data values). If the sample is completely homogeneous with respect to a certain feature, the entropy is zero for that feature (e.g. if all patients have the same age the entropy with respect to the feature ‘age’ is zero) and if the sample is an equally divided it has an entropy of one (e.g. if all patients have different age values, then entropy of the feature ‘age’ is one). Given a set S of adherence and non-adherence observations/examples, the entropy of set S relative to this binary classification is E(S) = − p(Ad)log p(Ad) – p(NAd)log p(NAd), where Ad denotes adherence and NAd refers to non-adherence, and function ‘p’ is the probability function.

As mentioned before, selection of an attribute to test at each node when constructing a decision tree requires that we choose the most useful attribute for classifying adherence versus non-adherence cases. We use information gain to find such a node. Information gain measures how well a given attribute separates the training examples according to their target classification. This measure is used to select among the candidate features at each step while expanding a partially constructed tree [8]. Information gain measures the expected reduction in entropy where values (f) is the set of all possible values for baseline feature ‘f’, and Sv the subset of S for which attribute f has value ‘v’.

$$Gain(S,f)=Entropy(S)-\sum_{v\in Values(f)}\frac{|Sv|}{S}Entropy(Sv)$$

The first term in this equation is the entropy of the original collection S and the second term is the expected value of the entropy after S is partitioned using attribute ‘f’. The information gain is in fact the expected reduction in entropy caused by partitioning the examples according to the feature ‘f’.[8]

Multilayer perceptron (MLP) classifier is a feedforward artificial neural network model utilizing supervised techniques. The k-NN classification algorithm classifies data samples by majority vote of its neighbors assigning the most common class among its k nearest neighbors.

Results

Out of 16 patients who provided consent for this study, only 7 utilized the RMS technology and took daily measurements regularly. These 7 patients were considered adherers. Data from the baseline measures were used to develop a context-sensitive prediction algorithm that projected whether or not non-adherence could be predicted in advance. Baseline demographic and clinical characteristics of users and non-users were comparable for a majority of sociodemographic and clinical factors (Table 1).

Table 2 shows various accuracy measures per class as well as overall. From a machine learning point of view, the problem considered in this study is a binary classification problem with two class labels, 'use' and 'non-use'. The table illustrates true positive (TP) rate, false positive (FP) rate, precision, recall, F-measure, and area under the curve (AUC) for each class and the overall predictions of the two classes. The results are based on a leave-one-subject-out cross validation analysis and uses only prominent features/attributes identified by the attribute selection software algorithm.

First, a decision tree classifier is developed which has a built-in feature selection algorithm that first finds prominent features prior to creating the decision rules. The decision tree approach utilizes a wrapper method to find a good subset of attributes for inclusion in the final decision tree. The feature selection method uses a best-first search strategy. For the current study, a total of 682 attribute subsets were evaluated prior to converging to a solution. The decision tree classifier had both precision and recall of 87.5%, and an F-score of 76.2% for predicting use of RMS. The attribute selection algorithm chose two attributes as being most informative in constructing the decision tree model. Those attributes include (1) Having or not having HF specialty care; (2) Having or not having an implantable cardioverter defibrillator. The majority of the patients classified as users of RMS had neither HF special care nor an implantable defibrillator.

Secondly, more complicated classifiers are used to build models for predicting access to RMS. A correlation-based feature selection algorithm is used to find prominent features prior to creating the classifiers [9]. This approach ranks features based on the correlation with the event of interest which is the adherence to the RMS in our case. The same two attributes (i.e., having HF specialty care and implantable defibrillator) are found as most significant in predicting adherence to use of RMS.

Multilayer perceptron (MLP) classifier is a feedforward artificial neural network model utilizing supervised techniques. The MLP classifier had overall precision and recall of 90.3% and 87.5% respectively, and an F-score of 87.5%. On the other hand, a k-NN classifier is used to predict the use of RMS by patients. The k-NN algorithm classifies data samples by majority vote of its neighbors assigning the most common class among its k nearest neighbors. The k-NN classifier had overall precision and recall of 94.5% and 93.8% respectively, and an F-score of 93.8%. This classifier is more accurate than the decision tree and MLP models.

We further report the area under the ROC curve (RUC), which is an accuracy measure that demonstrates to which extent our model is making an informed decision. While an area of 1 represents a perfect test, any value between 0.9–1 is considered an excellent accuracy which was achieved by our k-NN classifier in our experiment. It equivalently means that if we randomly pick one instance from each user and non-user group, our model will be able to discriminate between them correctly with a chance of 0.92 (see Table 2).

Discussion

The overall goal of this study was to distinguish between users (i.e. adherers) and non-users (i.e. non-adherers) of RMS using advanced data analytics in a cohort of patients with HF. Specifically, we aimed at determining whether certain user characteristics (i.e. personal and clinical variables) predict use of RMS using context-aware prediction algorithms [4]. Our findings showed that users were more likely to have non-HF specialty based care and an automatic internal cardioverter defibrillator; these characteristics were identified by our attribute selection algorithm. Likewise, we found that the RMS platform we used (i.e., WANDA-B) showed high levels of accuracy of the machine learning algorithm in predicting ‘use’ and ‘non-use’ of RMS, which is similar to other studies that examined the clinical outcome prediction accuracy of RMS in patients with HF [10]. The use of high accuracy measures of RMS is essential when these systems are clinically implemented in larger chronic HF patient population.

Our data support that RMS use was higher in patients who did not receive care from a healthcare provider with HF specialty. Adherence with use of RMS in patients not receiving care from HF specialists is likely related to the fact that these patients needed additional sources of motivation to help them engage in self-care behaviors. Patients who are managed by HF specialists receive this motivation from clinic staff and providers who place greater emphasis on educating and motivating patients to engage in self-care behaviors as part of the HF chronic disease management model [11]. Part of the recommendations for clinicians providing care to patients with HF is empowering them to engage in self-care which includes awareness of and monitoring for changes in their signs and symptoms of HF [12]; the RMS platform that was tested for this study was designed to achieve this goal. Unfortunately, physician education about self-care and how to instruct patients in self-care is rarely provided in either medical school or house staff curricula [12].

Our findings also showed that participants who had an internal cardioverter defibrillator were more likely to use the RMS. Several large scale clinical trials have supported the effectiveness of RMS in improving outcomes through early detection and management of clinical events among patients with cardiac implantable electronic devices [13–15]. Clearly, care facilitated by RMS has the potential to enable early detection of key clinical symptoms indicative of worsening overall health and allows healthcare providers to offer surveillance, advice, and triggers early implementation of strategies to enhance adherence behaviors [16]. Healthcare providers who are aware of the benefits of RMS are more likely to communicate this information to their patients and motivate them to improve their self-management skills. Likewise, patients with cardiac implantable electronic devices were likely more motivated to exhibit and maintain goal-directed behavior to reduce the probability that they will experience a noxious event [10]. This naturalistic decision making process is the hallmark of self-care where patients make choices on behaviors that maintain physiologic stability [12].

Motivation and intention are very important factors for new technology users [17]. Previous investigations by our research team demonstrated that older adults showed interest to learn health technology with support from their healthcare providers and family members to improve their self-management skills [18]. The self-care behaviors that were supported through the use of the RMS platform designed for the current study included daily weighing and awareness and reporting of signs and symptoms of worsening HF. Clearly, our data support the need to provide older patients with HF, who are often faced with greater challenges when it comes to learning and assimilating use of RMS, with education and counseling to enhance conviction and self-confidence and facilitate self-care behaviors and consequently improve the likelihood of using RMS in this vulnerable population [9].

Our study has some limitations. This is a small scale pilot study in a homogeneous sample of older patients with chronic HF being seen at a tertiary care facility. Our findings cannot be generalized to an adult patient population with HF. The study used a single-arm or non-randomized design in which everyone enrolled received the RMS. Due to the lack of a control group, the results can be skewed due to the probability of selection bias. However, the study was conducted with the most vulnerable patient population which may often have been excluded in large scale trials. In spite of these limitations, the results of this study illustrate areas in which research is needed to inform greater adoption of RMS in older patients with HF. Future studies should incorporate a control group and larger sample. Finally, clinical trials are needed to determine the effect of HF provider type and cardiac implantable electronic devices on actual adherence to use of RMS.

The generalization problem, in machine learning community, is strongly related to the overfitting issue with machine learning algorithms. Overfitting occurs when a high-dimensional feature space is extracted from a small dataset. When a model over-fits the training dataset, it usually fails to correctly classify the un-seen instances. Throughout this study we have taken this issue into consideration and used the existing machine learning techniques and evaluation methods that are designed to avoid overfitting (and therefore construct a more generalized predictor). Before creating the predictor, we perform feature selection, a dimensionality reduction technique that aims to provide balance between the training data size and the number of features extracted from the training instances. Feature selection reduces the training bias of the constructed predictor resulting in a more generalizable model with better performance against unseen data instances. Among the 200 features initially extracted from the collected data, the feature selection algorithm picked only two prominent instances. As a result, the adherence prediction model is less likely to be affected by the abundant and irrelevant features. Furthermore, in our evaluations, we used leave-subject-out cross validation method which iteratively excludes a portion of dataset (e.g., one-tenth of the initial dataset) from the training phase, and later uses those instances (i.e., un-seen instances) for measuring the prediction accuracy of the model created in that iteration. At the end, an average accuracy achieved over all iterations is reported. This result is more dependable, especially with small datasets, since not only the test and training dataset are separated, but also the entire dataset is used once for testing the model generated by the other portion of the data.

Conclusion

Health technology has dramatically advanced. Today we are in an era where RMS are used to enhance the care of patients with chronic disease conditions such as HF [10]. To determine user characteristics and clinical specific characteristics associated with use of such health devices can help clinicians and researchers better develop RMS that will be used by all patients and that could ultimately improve health outcomes. Our preliminary data show that a small set of baseline attributes is sufficient to predict subgroups of patients who had a higher likelihood of using RMS. To our knowledge, this is the first study to use contextual features to predict patient adherence to use of RMS technology. This approach has a number of potential advantages such as: (1) this approach provides insight into what patients we should further focus to improve their adherence to RMS. In fact, patients with only minimal likelihood of adherence many need to be approached in a different way than typical screening and enrollment strategies in order to include them in clinical studies. The patient may further require self-care education as well as education about benefits of RMS technology in enhancing their quality of life and clinical outcomes; and (2) identifying appropriate method to refine RMS technology such that a broader patient population can benefit from advantages of these interventions. While our findings shed light on potential end-users more likely to benefit from RMS-based interventions, additional research in a larger sample is warranted to better explicate the impact of user characteristics on actual exposure to the use of these technologies.

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Reference List

1. Evangelista LS, Lee J, Moore A, Motie M, Ghazemzadeh H, Sarrafzadeh M, Mangione C. Examining the effects of remote monitoring systems on activation, self-care, and quality of life in older patients with chronic heart failure. J Cardiovasc Nurs. 2015; 30:51–57. [PubMed: 24365871]
2. Desai AS. Home monitoring heart failure care does not improve patient outcomes: Looking beyond telephone-based disease management. Circulation. 2012; 125:828–836. [PubMed: 22331920]
3. Schneider F, van Osch L, Schulz D, kremer S, de Vires H. The influence of user characteristics and a periodic email prompt on exposure to an internet-delivered computer-tailored lifestyle program. J Med Internet Res. 2012; 14:e40. [PubMed: 22382037]
4. Song Y, LUY. Decision tree methods: applications for classification and prediction. Shanghai Arch Psychiatry. 2015; 27:130–135. [PubMed: 26120265]
5. Suh, Mk, Evangelista, LS., Chen, V., Nahapetian, A., Figueras, F., Sarrafzadeh, M. WANDA B: Weight and activity with blood pressure monitoring system for heart failure patients. IREHSS. 2010:1–10.
6. Suh, Mk, Chen, CA., Woodbridge, J., Tu, M., Kim, J., Nahapetian, A., Evangelista, L., Sarrafzadeh, M. A remote patient monitoring system for congestive heart failure. J Med Systems. 2011; 35:1165–1179.
7. Gell-Mann M, Lloyd S. Information measures, effective complexity, and total information. Complexity. 1996; 2:44–52.

8. Kent JT. Information gain and a general measure of correlation. Biometrika. 1983; 70:163–173.
9. Paradis V, Cossette S, Frasure-Smith N, Heppell S, Guertin MC. The efficacy of a motivational nursing intervention based on the stages of change on self-care in heart failure patients. J Cardiovasc Nurs. 2010; 25:130–141. [PubMed: 20168193]
10. Alshurafa N, Eastwood JA, Pourhomayoun M, Liu JJ, Sarrafzadeh M. Remote health monitoring: Predicting outcome success based on contextual features for cardiovascular disease. Conf Proc IEEE Eng Med Biol Soc. 2014:1777–1781. [PubMed: 25570321]
11. Baker DW, Asch SM, Keesey JW, Brown JA, Chan KS, Joyce G, Keeler EB. Differences in education, knowledge, self-management activities, and health outcomes for patients with heart failure cared for under the chronic disease model: the improving chronic illness care evaluationDifferences in education, knowledge, self-management activities, and health outcomes for patients with heart failure cared for under the chronic disease model: the improving chronic illness care evaluation. J Card Fail. 2005; 11:405–413. [PubMed: 16105630]
12. Riegel B, Moser DK, Anker SD, Appel LJ, Dunbar SB, Grady KL, Gurvitz MZ, Havranek EP, Lee CS, Lindenfeld J, Peterson PN, Pressler SJ, Schocken DD, Whellan DJ. on behalf of the American Heart Association Council on Cardiovascular Nursing. State of the science: Promoting self-care in persons with heart failure: A scientific statement from the American Heart Association. Circulation. 2009; 120:1141–1163. [PubMed: 19720935]
13. Ricci RP, Morichelli L, Onofrio A, Cal L, Vaccari D, Zanotto G, Curnis A, Buja G, Rovai N, Gargaro A. Effectiveness of remote monitoring of CIEDs in detection and treatment of clinical and device-related cardiovascular events in daily practice: the HomeGuide Registry. Europace. 2013; 15:970–977. [PubMed: 23362021]
14. Crossley GH, Boyle A, Vitense H, Chang Y, Mead RH. The CONNECT (Clinical Evaluation of Remote Notification to Reduce Time to Clinical Decision) Trial: The value of wireless remote monitoring with automatic clinician alerts. JAMA. 2011; 57:1181–1189.
15. Varma N, Epstein AE, Irimpen A, Schweikert R, Love C. for the TRUST Investigators. Efficacy and safety of automatic remote monitoring for implantable cardioverter-defibrillator follow-up: The Lumos-T Safely Reduces Routine Office Device Follow-Up (TRUST) Trial. Circulation. 2010; 122:325–332. [PubMed: 20625110]
16. Wakefield BJ, Holman JE, Ray A, Scherubel M, Burns TL, Kienzle MG, Rosenthal GE. Outcomes of a home telehealth intervention for patients with heart failure. J Telemed Telecare. 2009; 15:46–50. [PubMed: 19139220]
17. Evangelista L, Doering L, Dracup K, Westlake C, Hamilton MA, Fonarow G. Compliance behaviors of elderly patients with advanced heart failure. J Cardiovasc Nurs. 2003; 18:197–206. [PubMed: 12837010]
18. Lee JA, Nguyen AL, Berg J, Amin A, Bachman M, Guo Y, Evangelista L. Attitudes and preferences on the use of mobile health technology and health games for self-management: Interviews with older adults on anticoagulation therapy. JMIR Mhealth Uhealth. 2014; 2:e32. [PubMed: 25098413]

Table 1

Baseline Sociodemographic and Clinical Characteristics (N =16)

	All Participants (N=16)	RMS* users (n = 7)	RMS non-users (n =9)	Sig.
Age, years (Mean±SD)	71.5 ± 6.5	73.6 ± 6.2	69.3 ± 6.8	.579
Male, N (%)	8 (50.0%)	3 (42.9%)	5 (55.6%)	.779
Race, N (%)				.724
Hispanic	6 (37.5%)	2 (28.6%)	4 (44.4%)	
White	8 (50.0%)	4 (57.1%)	4 (44.4%)	
African American	2 (12.6%)	1 (14.3%)	1 (11.1%)	
Married, N (%)	12 (75.0%)	5 (71.4%)	7 (77.8%)	.525
Education, N (%)				.926
≤ High school	7 (43.8%)	3 (42.9%)	4 (44.4%)	
Some college	7 (43.8%)	3 (43.9%)	4 (44.4%)	
Completed college	2 (12.5%)	1 (14.3%)	1 (11.1%)	
Ejection fraction, % (Mean±SD)	25.0 ± 4.9	24.3 ± 4.7	25.7 ± 5.2	.407
Peak VO_2, mg/kg/min (Mean±SD)	13.2 ± 3.0	12.6 ± 3.2	13.8 ± 2.7	.191
Body mass index (Mean±SD)	26.5 ± 3.2	26.3 ± 3.0	26.8 ± 3.4	.977
Charlson Comorbidity Index (Mean±SD)	3.5 ± 1.4	3.7 ± 1.5	3.3 ± 1.3	.220
NYHA class, N (%)				.395
Class 2	9 (56.3%)	5 (71.4%)	4 (44.4%)	
Class 3	7 (43.7%)	2 (28.6%)	5 (55.6%)	
Hypertension N (%)	7 (43.7%)	3 (43.9%)	4 (44.4%)	.957
Coronary artery disease N (%)	9 (56.3%)	4 (57.1%)	5 (55.6%)	.837
Diabetes mellitus, Type 2 N (%)	8 (50.0%)	3 (42.9%)	5 (55.6%)	.454
Overweight or Obese, N (%)	5 (31.3%)	3 (42.9%)	2 (22.3%)	.233
Internal Cardioverter Defibrillator, N (%)	9 (56.3%)	5 (71.4%)	4 (44.4%)	.057
Hx smoking (previous smoker) N (%)	8 (50.0%)	4 (57.1%)	4 (44.4%)	.648
Healthcare Provider, HF specialist N (%)	10 (62.5%)	6 (85.1%)	4 (44.4%)	.048*

RMS = Remote Monitoring Systems;

*p < 0.50

Table 2

Accuracy measures of different machine learning algorithms in predicting ‘use’ and ‘non-use’ of remote monitoring systems

	TP Rate (tp)	FP Rate (fp)	Precision	Recall	F-Measure	AUC
‘Use’(Decision Tree)	85.7%	11.1%	85.7%	85.7%	85.7%	0.76
‘Non-Use’(Decision Tree)	88.9%	14.3%	88.9%	88.9%	88.9%	0.76
Overall (Decision Tree)	87.5%	12.9%	87.5%	87.5%	87.5%	0.76
‘Use’(k-NN)	100%	11%	87.5%	100%	93.3%	0.92
‘Non-Use’(k-NN)	88.9%	0%	100%	88.9%	94.1%	0.92
Overall (k-NN)	93.8%	0.05%	94.5%	93.8%	93.8%	0.92
‘Use’(MLP)	100%	22%	77.8%	100%	87.5%	0.84
‘Non-Use’(MLP)	77.8%	0%	100%	77.8%	87.5%	0.84
Overall (MLP)	87.5%	0.10%	90.3%	87.5%	87.5%	0.84

TP = true positive; FP = false positive; AUC = area under curve