Remote Patient Monitoring: What Impact Can Data Analytics Have on Cost?

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ABSTRACT

While significant effort has been made on designing Remote Monitoring Systems (RMS), limited research has been conducted on the potential cost savings that these systems offer in terms of reduction in readmission costs, as well as the costs associated with human resources involved in the intervention process. This paper is particularly interested in exploring potential cost savings that an analytics engine can provide in presence of intelligent back-end data processing and machine learning algorithms against conventional RMS that operate based on simple thresholding approaches. Using physiological data collected from 486 heart failure patients through a clinical study in collaboration with the UCLA School of Medicine, we conduct a retrospective data analysis to estimate prediction accuracy as well as associated costs of the two remote monitoring approaches. Our results show that analytics-based RMS can reduce false negative rates by 61.4% while maintaining a false positive performance close to that of conventional RMS. Furthermore, the proposed analytics engine achieves 61.5% reduction in the overall readmission costs.

Categories and Subject Descriptors

J.3 [**Computer Applications**]: Life and Medical Science—*Health*; H.1.2 [**Information Systems**]: Models and Principles—*User/Machine Systems Human information processing; Human factors*

General Terms

Design, Measurement, Verification

Keywords

Remote Monitoring Systems, Heart Failure, Cost Analysis, Readmission, Intervention

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1. INTRODUCTION

Recent technological advances have resulted in a new healthcare intervention approach called Remote Monitoring Systems (RMS), which provide continuous monitoring of patients beyond physical borders. Development of RMS is the result of significant advancements in electronics, pervasive sensors, and communications over the last decade. RMS can frequently monitor physiological status of patients using heterogeneous sensors such as blood pressure, weight, blood glucose, and/or physical activity sensors in order to shift medical services from hospital and clinical settings to an in-home monitoring scenario [1]. RMS are recognized as an alternative intervention approach that may significantly reduce healthcare costs and improve quality of medical services [2] for patients with Chronic Heart Failure (CHF) [3], diabetes [4, 5], Chronic Obstructive Pulmonary Disease (COPD) [6] and other chronic conditions [7, 8].

Studies show that successful deployment of RMS can save approximately $81 billion in annual medical costs by improving healthcare efficiency and safety [9]. Based on these results, much engineering research has focused on developing efficient system architectures [10] or accurate data analysis methodology for RMS [1, 11, 12]. However, it is yet unclear if RMS provide quality services in a cost-effective manner when they are indeed deployed in a natural setting (i.e., patient's home).

As of October 2012, the US government began implementing the Medicare Readmission Reduction Program, which levies financial punishment on hospitals with high readmission rates. Statistics show that nearly 20% of insured patients are readmitted to hospitals within 30 days after discharge mainly due to many correctable sources of poor health care services, which incurred approximately $17 billion in 2009 [13, 14]. Reduction in the readmission rate is typically achieved by increasing interactions between patients and clinicians through early interventions.

Conventional RMS rely on standard medical approaches [15]; physiological data collected by RMS are evaluated by clinical professionals, or are processed based on simple threshold-based methods to trigger alerts [3, 16] based on which an intervention may be initiated. For instance, an alert can be triggered when a patient's heart rate exceeds 120 bpm, which may result in an intervention by clinicians. However, this method suffers from static thresholds that prevent the system from being flexibly configured based on the constraints of the systems (e.g. number of available clinical staff); there exist far too many thresholds to be configured, which cannot be adjusted to find a setting that minimizes the total cost. These motivations raise the question of whether or not conventional RMS can predict adverse events with sufficient accuracy in a cost-effective manner. Furthermore, this necessitates development of reconfigurable predictive modeling that can adjust false positive and false negative rates according to the constraints of the system. To the best our knowledge, this study is the first attempt to address cost benefits of analytics-based intervention using RMS.

Based on the proposed data analytics engine, which employs penalty-sensitive classifiers[1], this paper aims to investigate (i) readmission prediction mechanisms of the two remote monitoring systems, i.e., how to classify physiological measurements as 'positive' or 'negative'; (ii) how accurate each remote monitoring system is in terms of false positive and false negative rates?; and (iii) how these predictions translate into medical costs?

2. RELATED WORKS

Several works exist involving remote patient monitoring. The purpose of these remote monitoring and telemedicine systems is to reduce the potential costs to patient care [1]. Furthermore, such systems [2, 17, 3, 4, 18, 5, 6] discuss the potential of improving patient care with extensive monitoring techniques, but lack a comprehensive cost analysis to validate the effectiveness of the monitoring techniques. In particular, the systems must provide information in a way to reduce the workload, providing potential savings [9, 1], but do not explicitly denote the cost figures.

Meanwhile, several works, such as [19] and [20] analyze tele-medicine and remote health monitoring systems from a cost-effectiveness standpoint. Indeed, [19] concluded that comprehensive research on cost-effectiveness of these approaches needs to be conducted, while [20] suggests further work needs to be done beyond simple cost-effectiveness and delve into further cost savings from adopted usage.

Several tele-medicine systems have investigated the cost savings of using the systems [21, 22, 23]. [23] examined well-being metrics for the patients, such as fuel and distance traveled savings, days missed at work, and general family expenses effected by necessary treatments of patients at the University of Arkansas for Medical Sciences. [22] studies tele-medicine intervention and its cost effectiveness to help patients with hypertension. [21] measures the cost-effectiveness of interventions by developing a ratio against the quality adjusted life-years. The intervention used tele-medicine in a rural setting for depression treatment where no psychiatrist or psychologist existed on site. The work concluded that the intervention was effective, but was quite costly, on the order of $85,643 per quality adjusted life-years.

3. PRELIMINARIES

This section provides an overview of both conventional RMS and analytics-based RMS. It also discusses the clinical data that are used for the analysis in the paper. This paper uses heart failure as the pilot application where the goal of remote monitoring is to prevent hospital readmissions.

[1]It is known as cost-sensitive classifier in the field of machine learning. This paper uses the term *penalty-sensitive* in order to avoid confusion with the term *medical cost*, which is frequently used in this paper.

Table 1: Typical alerts generated by conventional RMS

Label	Description	Priority
A_1	$HR \geq 100$ bpm	Medium
A_2	$HR \geq 120$ bpm	High
A_3	$HR \leq 55$ bpm	High
A_4	Systolic $BP \leq 100$ mmHg	Low
A_5	Systolic $BP \leq 80$ mmHg	Medium
A_6	Systolic $BP \geq 160$ mmHg	Medium
A_7	W increase of 2 lbs over 1 day	Low
A_8	W increase of 3 lbs over 3 days	Medium
A_9	W increase of 3 lbs over 1 days	High

3.1 Remote Monitoring Systems

Remote monitoring systems for readmission reduction aim to gather physiological data and analyze these data to provide insight into which patients might be at risk for being readmitted. The data are gathered remotely and are hypothesized to correlate with symptoms of critical patients with heart failure [15]. These parameters may include weight (W), blood pressure (BP), heart rate (HR), and self-reported questionnaires regarding heart failure symptoms.

An RMS may include two major tiers: data gathering and data processing as shown in Figure 1. Patients are given wireless devices that measure weight, blood pressure, and heart rate, which are wirelessly transmitted via Bluetooth to a gateway such as a cellular gateway or a smartphone. The wireless capabilities are important in order to enhance patient compliance. The gateway then transmits the data to a secure database for data storage and processing. From this database, clinical professionals can view/search past readings and patient's data, and react to abnormal readings that may be an indication of an adverse event such as a hospital readmission.

3.2 Conventional RMS

Conventional RMS for adverse event detection rely on a threshold-based approach. Based on predefined threshold values, an alert is generated when a physiological measurement is out of the acceptable range, and notify the nurses to intervene on patients and possibly prevent readmission by providing adequate medical services. For example, a patient's heart rate may be considered normal when the value lies between 50 bmp and 120 bpm. As a result, an alert is generated when the patient's heart rate deviates from this predefined range. The alerts are usually labeled as low-, medium-, and high-priority depending on the degree of deviation from the threshold. The threshold values can be potentially personalized for each patient according to the suggestion made by physicians. In the dataset used in this paper, a total of 26 different alerts based on weight, blood pressure and heart rate values are considered. A partial list of the alerts used in this study is provided in Table 1. The decision on the type of alerts (low-, medium-, and high-priority) is typically made by clinicians. This decision process is dynamic, which may change over time and may also vary among different clinicians. In this paper, it is assumed that clinicians provide intervention when the triggered alert is high. In other words, it assumes that in conventional RMS 'high' priority alerts are classified as 'positive' (require an intervention), and the other two types of alerts (i.e., 'medium'

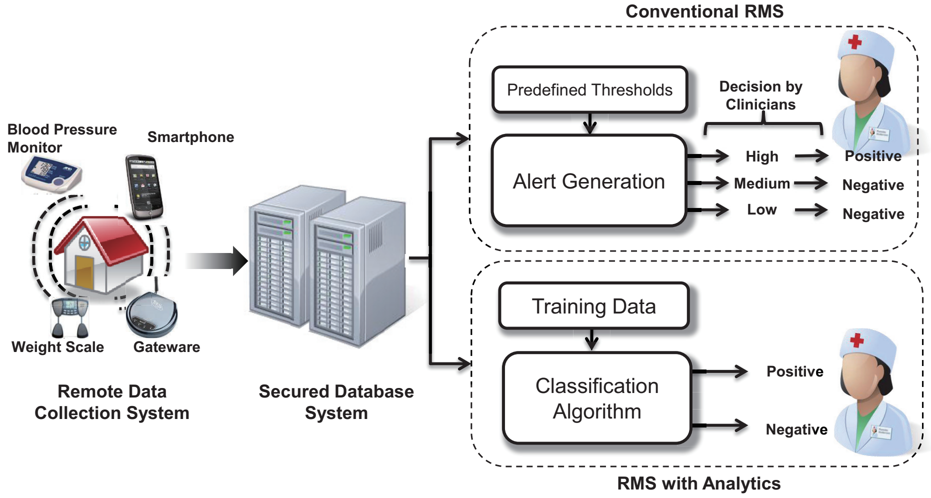

Figure 1: Conventional and analytics-based RMS

and 'low') are classified as 'negative' (do not require an intervention).

3.3 Analytics-based RMS

A remote monitoring system with analytics uses advanced machine learning algorithms for readmission prediction. The analytics engine is what drives the ability of the RMS to effectively assess the risk factors for adverse events in patients and allow the call center nurses to effectively intervene in such patients' treatments. It is upon this analytics framework in which the cost-effective system has been developed. The core of the analytics engine is a binary classifier which classifies physiological data as 'positive' or 'negative'. More details regarding the analytics engine is described in Section 4.3. Figure 1 shows a system architecture of RMS platforms that are discussed in this paper. Similar to the conventional RMS, in an analytics-based RMS classifying a measurement as 'positive' indicates that the remote monitoring system has predicted an impending readmission and an intervention is needed to prevent the readmission. The analytics not only use alerts triggered by conventional RMS but also extracts a number of statistical features, listed in Table 2, that are fed to the classification algorithm.

3.4 Clinical Data

The data used for the analysis are gathered through an ongoing clinical study that targets 1500 heart failure patients. The study, which is planned to end by March 2014, is a collaboration of UCLA, UC Davis, UC San Francisco, UC Irvine, UC San Diego, and Cedar Sinai hospital. In this paper, data collected between October 2011 and April 2013 from patients in the intervention arm, which includes those patients who are provided with remote monitoring devices such as wireless blood pressure monitors and weight scales, are used. The dataset includes 486 patients. The data collection system generated a dataset containing the history of all alerts and its raw sensory values measured by patients. Furthermore, an adverse event report, which includes the history of readmission, is used for ground truth labeling (i.e., either 'positive' or 'negative') of all the alerts. An alert or a measurement was labeled as 'positive' if the patient was readmitted within 6 days from the day of the measurement.

4. READMISSION PREDICTION

As stated previously, the goal is to compare conventional RMS and analytics-based RMS in terms of their readmission prediction performance and the associated medical costs. The accuracy of readmission prediction for the two remote monitoring models is performed in a retrospective manner. This paper assumes that the prediction algorithm aims to predict readmission in a time frame of w days prior to the readmission date. Therefore, alerts generated within w days prior to the readmission should carry critical information regarding the patient's readmission.

4.1 Prediction Mechanism

Conventional RMS rely on threshold-based alerts that categorize severity of heart failure symptoms into high-, medium-, and low-priority. As discussed earlier, this paper assumes that a conventional RMS will classify high-priority alerts as 'positive' and other types of alerts as 'negative'.

An exemplary scenario of readmission prediction using conventional RMS is illustrated in Figure 2. The figure depicts a patient's possible interaction with RMS in four days. The patient's physiological measurements have triggered alerts in the first two consecutive days (i.e., 'Day 1' and 'Day 2'), followed by one day of missing data on 'Day 3'. Then, the patient is being readmitted (denoted by 'R') on 'Day 4'. This example considers a window size of $w = 3$ days.

The two alerts generated on the first day have high and medium priorities denoted by 'H' and 'M' (i.e., second row with label *Alert Type*). In reality, RMS may generate more than one alert on a specific day. Multiple alerts may be a result of taking multiple measurements of the same vital signs (e.g., taking weight several times), or a result of heterogeneous measurements exceeding their predefined thresholds (e.g., both heart rate and systolic blood pressure are out of the acceptable ranges). In either case, only a single inter-

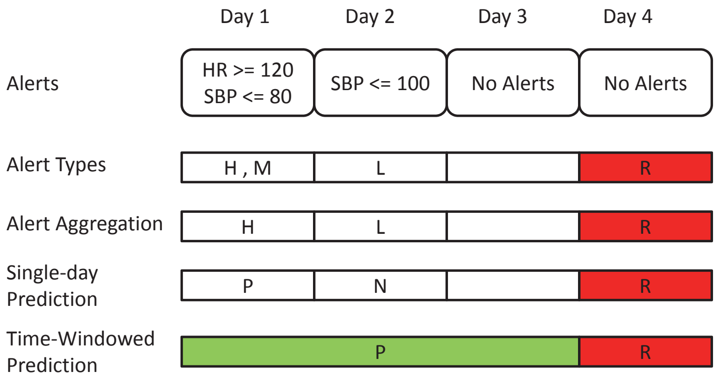

Figure 2: Adverse event prediction using conventional RMS

vention is conducted by the call center nurses in responding to all the alerts generated for a patient on a particular day. Therefore, in the analysis, we aggregate all alerts of the same patient on a specific day by considering only the highest priority alerts (e.g., the 'H' alert on 'Day 1') and discarding the remaining ones (e.g., the 'M' alert on 'Day 1'). We denote a prediction made on each day as *single-day prediction*. As a result, the single-day prediction on 'Day 1' classifies the alerts as 'positive', which is denoted by 'P' in the fourth row. In a similar manner, the low priority alert on 'Day 2' is classified as 'negative', denoted by 'N'. Then, these single-day predictions are aggregated over 3 days to provide *time-windowed prediction* under a specific rule, which will be discussed in the following subsection.

Analytics-based RMS uses machine learning algorithms for single-day predictions. The time-windowed prediction is identical for both conventional and analytics-based models. Furthermore, the analytics-based system takes as input both alters and raw measurements and computes a set of statistical features from these data prior to executing the classification algorithm.

4.2 False Negatives and False Positives

The single-day prediction and time-windowed prediction compute false/true positive alerts and false negative readmissions, which may incur unnecessary nursing costs and readmission costs, respectively. This mechanism helps convert the prediction accuracy performance of RMS into the associated medical costs. Although further discussions about these costs will be made in Section 5, for a brief introduction, the readmission cost is computed based upon the number of readmission events that were not predicted by the system (i.e., false negative readmissions), and the nursing cost is associated with the total number of instances that required intervention (i.e., false positive and true positive alerts).

In order to compute the nursing cost, one must compute the amount of time that the nurses spent on interventions. Since the nurses respond only to the measurements predicted as 'positive', the false positive and true positive rates must be computed. Thus, single-day predictions are used to calculate false positive and true positive rates.

The readmission cost is computed based on the number of readmission events that were not predicted by the RMS in a w-day window. Unlike general classification problems, readmission prediction in remote monitoring environments involves prediction in a time window. For example, when a

Table 2: features used by analytics engine

No.	Description
1	Weight of the issued alert
2	Sum of the alert weights within the past 5 days
3	Absolute weight gain in last seven days
4	Normalized weight gain in last seven days
5	Raw Heart Rate Value

nurse receives a positive alert, she/he provides intervention to further investigate the physical status of the associated patient. Under an assumption that each intervention successfully prevents any possible readmission within w days, positive or negative alerts that follow an intervention do not further effect the results of predicting the readmission. This implies that having at least one positively classified alert within w days prior to the actual readmission must be considered as a successful prediction. Thus, we further process single-day predictions and combine them to generate time-windowed predictions. The time-windowed prediction labels a window as 'positive' if there exists at least one positive single-day prediction within the window, and 'negative' otherwise. According to this rule, the three-day time-windowed prediction in the example in Figure 2 is labeled as 'P'.

In summary, the RMS platform (either conventional and analytic-based model) produces (i) false positive and true positive alert rates based on single-day prediction (denoted as fp and tp, respectively) and (ii) false negative readmission rates based on time-windowed prediction (denoted as $\widehat{fn}$).

4.3 Prediction using Analytics

The proposed analytics-based prediction model begins with feature extraction which extracts statistical features and alert-related features from the data. The conventional RMS model considers only the type (high, medium, and low) of the generated alerts, which can be considered as binary features (e.g., HR greater than 100 bpm or not), in order to make a decision for intervention. On the other hand, the proposed analytics-based model includes a number of statistical and physiological features in addition to those binary features associated with the alerts. For example, in order to consider the recent physiological status of the patient, the alert information of the patient in the past 5 days from the date of the issued alert is aggregated. To do so, high-, medium-, and low-priority alerts are assigned weights of 2, 1, and 0, respectively, and the sum of the alert weights of the past 5 days (including the weight of the issued alert) is considered as a feature. For another example, normalized maximum in the last 7 days, which is the percentage of the maximum weight gain in last 7 days compared to the the patient's weight on the date of the issued alert, is considered is calculated as a feature. Some of these added features are listed in Table 2.

Conventional RMS has a limitation that the system performance cannot be flexibly and predictably configured to the available clinical resources because the predefined positive and negative decision rule cannot be systematically and predictably adjusted. In order to provide a configurable analytics performance, the system employs a penalty-sensitive classifier based on a support vector machine (SVM) classifier. A penalty-sensitive classifier is a meta classifier that makes the standard classifier (e.g., SVM) penalty-sensitive by assigning misclassification penalties to the desired classes. As a result, the classifier selects a class that minimizes the expected penalty rather than the most likely class [24]. This work employs the *MetaCost* algorithm, which creates an additional layer of learning on top of the SVM to effectively minimize the desired penalty [25].

5. COST ANALYSIS

This section discusses how the readmission and nursing costs are derived from different prediction performances (i.e., false/true positive alert rates and false negative readmission rates) based on clinical and logistical data obtained from the conducted study. Then, this paper reports the associated medical costs at different prediction configurations of the proposed analytics-based model, and compares the results against the costs of the conventional method in Section 6.

The readmission cost C_r is computed as

$$C_r = \alpha \times \widehat{fn} \times N_r, \quad (1)$$

where α represents the cost of a single 6-month readmission. $\widehat{fn}$ represents false negative readmission rate computed based on time-windowed prediction, and N_r represents the number of readmissions. As a result, $\widehat{fn} \times N_r$ accounts for the number of readmission events that are not predicted within w days prior to readmission.

The nursing cost C_n can be computed as

$$C_n = \beta \times [(fp \times N_n) + (tp \times N_p)], \quad (2)$$

where β denotes nursing costs per intervention. fp and tp represent false positive and true positive alert rates computed based on single-day prediction, respectively. Furthermore, N_n and N_p represent the number of negatively and positively labeled (i.e., ground truth label) instances, respectively. As a result, $fp \times N_n$ computes the number of false positives and $tp \times N_p$ computes the number of true positives. Since nurses provide intervention for both false positive and true positive predictions, the total number of alerts that have been classified as positive is multiplied by β in order to compute the total nursing costs.

6. EXPERIMENTAL RESULTS

The remote monitoring system is currently in the midst of a two year on-going clinical study. A total of 486 patients enrolled between October 2011 and April 2013 were included

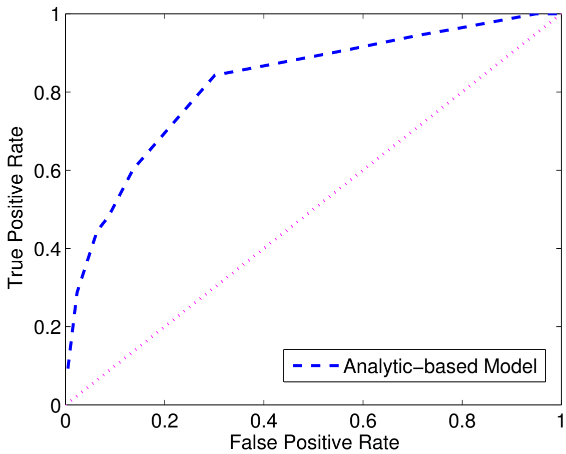

Figure 3: Readmission prediction performance of the proposed analytic model

in this experiment. A total of 12,680 alerts were generated as a results of monitoring these patients. This resulted in 6,435 aggregated alerts after applying the 'Alert Aggregation' process in Figure 2. This section reports the readmission prediction accuracy, the associated medical costs of the conventional RMS model, and those of the proposed analytics-based model.

6.1 Prediction Performance

The penalty-sensitive classifier can be configured to provide various detection performance. By carefully assigning the penalties (weights) for the binary classes, the penalty-sensitive classifier can analyze the entire range of the classification performance of the base classifier. Figure 3 illustrates the Receiver Operating Characteristic (ROC) curve of the proposed analytics-based model. The false negative rates for the missed readmissions are computed based on 6-day time-windowed prediction. The Area Under the Curve (AUC) of the ROC was 0.82.

Table 3 summarizes the false positive and true positive alert rates, and false negative readmission rates of the conventional RMS and the proposed analytics-based model at various configurations. The analytics-based prediction can reduce false negative readmission rates by 61.4% (from 24.1% to 9.3%) and enhances the true positive alert rate by 31.9% (from 68.0% to 89.7%) while maintaining almost the same false positive alert rates as conventional RMS. This implies that given the same amount of false alerts, the rate for producing true alerts has been increases and the rate of missed readmissions has been decreases, which can reduce nursing and readmission cost, respectively.

Figure 4 illustrates the readmission prediction results of 49 randomly selected readmission events based on the analytics-based model at $\widehat{fn} = 9.3\%$ and the conventional monitoring model (i.e., $\widehat{fn} = 24.1\%$). Each readmission is colored in 'red' if it was not predicted by the employed RMS model, and was left in 'white' otherwise.

6.2 Cost Analysis Parameters

In (1), α is a constant which represents 6-month readmission costs per hospitalization. The median 180-day inpa-

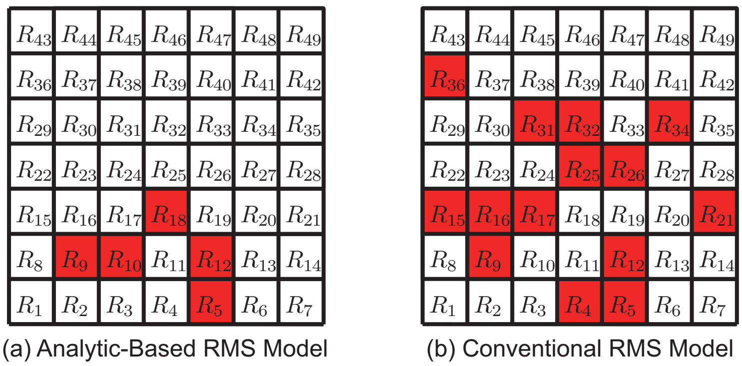

Figure 4: Illustration of readmission prediction of (a) the analytics-based model at $\widehat{fn} = 9.3\%$ and (b) the conventional model at $\widehat{fn} = 24.1\%$.

Table 3: Prediction accuracy of conventional RMS compared to analytics-based RMS

RMS	fp	tp	$\widehat{fn}$
Conventional	**56.4%**	**68.0%**	**24.1%**
Analytics	79.4%	94.0%	3.7%
Analytics	70.9%	92.7%	5.6%
Analytics	**56.7%**	**89.7%**	**9.3%**
Analytics	30.1%	77.8%	15.7%
Analytics	13.6%	53.4%	39.8%
Analytics	8.7%	40.6%	51.8%

tient cost for heart failure patients is \$13,463 according to the study in [26]. Given that the goal is to monitor patients for 6 months, we set $\alpha = \$13,463$.

The parameter β in (2) is computed based on the results of the conducted clinical study. Without loss of generality, this paper assumes that the annual salary of a nurse is fixed and is set to \$150,000. Since the clinical data used in this study was collected over about 18 months, (i.e., about 1.5 years) and a total of 3 nurses participated, the overall nursing cost is $\$150,000 \times 1.5 \times 3 = \$675,000$. We compute β by dividing this number by the total number of alerts (6435). Thus, the average nursing cost per intervention is \$104.90. Note that this intervention cost not only includes the cost on providing actual interventions (e.g., by a phone call) but also the cost for the associated activities such as retrieving relevant patient information prior to the intervention, documenting and logging the history of the intervention, participating in study-related meetings, and interacting with the technical support team for troubleshooting technology-related problems and data transmission issues. Thus, this nursing cost might be study-dependent and may vary from one setting to another.

6.3 Readmission and Nursing Costs

Based on the false negative readmission rates and false positive alert rates of conventional RMS in Table 3 and the parameters in Section 6.2, the readmission costs and nursing costs of conventional RMS are computed as \$350,038 and \$383,706, respectively. This results in a combined medical costs of \$733,744. Detailed cost information of the conventional and the analytic-based RMS is provided in Table 4.

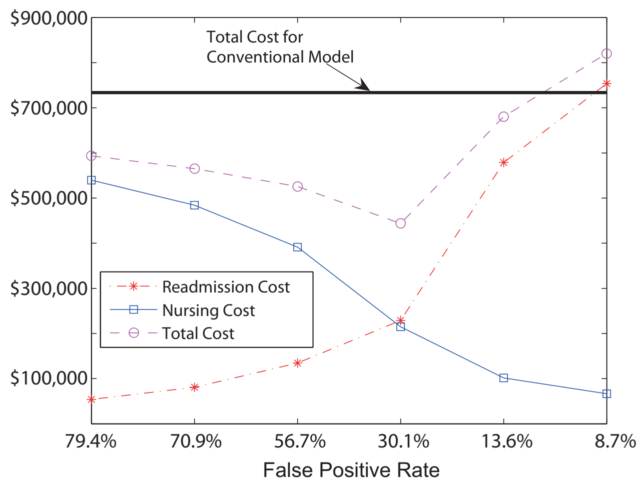

Figure 5: Readmission and nursing costs of analytics-based model as fp grows

Computed in a similar manner, the medical costs of analytics-based RMS are illustrated in Figure 5. For analytics-based RMS, the classification configuration of $\widehat{fn} = 9.3\%$ and $fp = 56.7\%$ (which has a fp close to that of conventional RMS) resulted in a readmission cost of \$134,630 and nursing costs of \$391,154. This results in a total medical cost of \$525,784. Thus with similar fp performance, the analytics-based model achieves a readmission cost saving of 61.5% (approximately \$207,960). Furthermore, the configuration of $\widehat{fn} = 15.7\%$ and $fp = 30.1\%$ provides the combined medical cost of \$443,696, which is approximately 40% lower than that of conventional RMS (i.e., \$733,744).

7. DISCUSSION AND FUTURE WORK

This paper reports readmission prediction performance and associated medical costs based on the data collected in a heart failure study. The nursing cost per intervention β in (2) may be improved in a commercial setting of RMS in various ways. The amount of required time per intervention may be formulated as a function of many parameters such as nurse expertise, the intervention procedure defined

Table 4: Performance comparison the two approaches

RMS Model	$\widehat{fn}$	fp	C_r	C_n	$C_r + C_n$
Conventional	**24.1%**	**56.4%**	**\$350,038**	**\$383,706**	**\$733,744**
Analytics	3.7%	79.4%	\$53,852	\$539,685	\$593,537
Analytics	5.7%	70.9%	\$80,778	\$484,196	\$564,974
Analytics	**9.3%**	**56.7%**	**\$134,630**	**\$391,154**	**\$525,784**
Analytics	15.7%	30.1%	\$228,871	\$214,825	\$443,696
Analytics	39.8%	13.6%	\$578,909	\$101,643	\$680,552
Analytics	51.8%	8.7%	\$753,928	\$66,399	\$820,327

by physicians, and technology infrastructure that facilities documentation of the intervention. For example, without a good technological infrastructure, nurses may need to use multiple systems to look up information they need for the intervention (e.g., patient history, medications), or to document the intervention after each call. The improvement on these work environmental settings may reduce the amount of average intervention time. In the conduced clinical study, reacting to the alerts was not only daily task for the call center nurses. They also participated in study-related meetings, interacted with technical staff to troubleshoot problems with monitoring devices, and extensively documented study-related logs.

The readmission cost C_r in (1) may be overestimated since it was assumed that all the predicted readmission events can be prevented. For example, in [27], a randomized pilot study shows that careful intervention may reduce readmission events by 56%. The intervention is a comprehensive multidisciplinary treatment that involves intensive teaching, a review of medication, early consultation with social services, dietary teaching, and close follow-ups after discharge [27]. However, the provided intervention was based on frequent face-to-face monitoring using video technology (i.e., telemedicine), which does not involve monitoring of patient's vital signals as offered in our work. Although this paper expects the prevention can be achieved more effectively and efficiently using the proposed monitoring system, there has been no randomized study of remote patient monitoring for congestive heart failure patients to the best knowledge of the authors. Nonetheless, the primary goal in this paper was to compare the two remote monitoring approaches. A lower rate of preventable readmissions may affect the cost values for both systems similarly.

This work used only physiological data such as blood pressure and weight measurements for readmission prediction. The remote monitoring system of the conducted study also gathered symptom questionnaires as part of daily measurements. These questionnaires are questions that require 'yes' or 'no' answers such as 'Have you had any light-headedness or dizziness in the last day?' or 'Have you noticed more swelling in the last day?'. Integrating features that are extracted from these questionnaires to further improve performance of the analytics engine is ongoing.

This study involves a subset of the data (e.g., both physiological data and readmission history), which involves instances that have resulted in an alert by the conventional RMS. The rationale behind this is (i) to focus the study on post-processing of the alerts generated by conventional RMS and (ii) to minimize the effect of missing data, which may be raised when analytics-based prediction is applied on the entire collected data rather than those associated with the alerts. The authors are currently working on using the entire dataset with effective missing data imputation mechanisms. Furthermore, the results of the analytics-based model in this paper are examined in a retrospective manner. Plans to conduct a two-arm clinical study such that patients in conventional RMS arm can be directly compared against those in analytics-based RMS is ongoing.

In this paper, we considered 'median' 180-day inpatient cost ($\$13,463$) for calculating readmission costs. The study in [26] also reports that the 'mean' 180-day inpatient cost, which is $\$22,505$. Our reason for using 'median' cost was that the 'mean' estimates are skewed by outliers. A more extensive and in-depth analysis is needed to determine which estimate ('mean' or 'median') is a better representative of the heart failure patient population. By setting $\alpha = 22,505$, the readmission costs will be $\$225,050$ and $\$585,130$ for analytics-based and conventional RMS respectively. This will result in a total medical costs of $\$616,203$ and $\$968,836$ for for analytics-based and conventional RMS respectively.

8. CONCLUSION

This paper discusses the potential cost savings that remote patient monitoring systems may offer by employing an advanced data analytics engine. The proposed analytics engine incorporates a penalty-sensitive classifier that offers various readmission prediction configurations. Based on the clinical data of 486 heart failure patients, the performance of the proposed method is compared against that of conventional RMS, which is based on a simple threshold-based approach. Experimental results report that the proposed analytic method reduces the false negative readmission rate by 61.4% while maintaining similar false positive alert rate compared to the conventional method. This allows 61.5% reduction in the overall readmission costs. This study introduces new insights on remote monitoring systems for their readmission prediction and the associated medical costs. This may enable extensive research opportunities including optimization of RMS for minimizing a specific medical cost class (e.g., readmission or nursing cost), or the overall medical costs.

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