Predictive Modeling of Emergency Hospital Transport using Medical Alert Pattern Data: Retrospective Cohort Study
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Abstract
Background: In the transition from a fee-for-service to a fee-for-value system, health care organizations (HCOs) are under pressure to keep patients healthy through preventive services and population health management. Predictive analytics based on the past health behavior of the patient population can be used to predict future risk of decline.

Objective: The objective of this study was to develop robust predictive models of impending emergency transports to the hospital based on enrollment and medical alert pattern data from subscribers of a Personal Emergency Response System (PERS) service. This enables targeting of clinical programs to members that need it the most.

Methods: De-identified medical alert pattern data of 551,127 subscribers to a PERS service were used. Multivariate logistic regression was performed on subscriber demographics, self-reported medical conditions, variables related to the care giver network and variables derived from up to one year of retrospective medical alert data. A 10-fold cross-validation scheme was used to predict transport to the hospital by emergency medical services in the next 30 days. Furthermore, the model performance was evaluated after retraining using up to 90 days of medical alert data, and using enrollment data only.

Results: Emergency hospital transport in the 30-day window was experienced by 2.4% of all subscribers. The area under the receiver operator characteristic curve (auROC) was 0.75 ± 0.01 in the validation cohorts. The model using up to 90 days of data resulted in auROC = 0.71 ± 0.01 and the model using enrollment data only resulted in auROC = 0.62 ± 0.01.

Conclusions: Our model for emergency hospital transport in subscribers of a medical alert service showed good discriminatory accuracy on retrospective validation data. While the model yields good discriminatory accuracy with up to 90 days of data, best performance is achieved using up to one year of medical alert data. The model using enrollment data only, without medical alert pattern data, does not perform as well. We are planning a prospective validation of the algorithm to determine the value of the predictive model in assisting HCOs with planning early interventions to avoid emergency department visits and hospitalizations.

Introduction
The Affordable Care Act has drawn attention to population health management as a model of care with great promise in reducing costs and improving health outcomes [1]. Population health management focuses on improving the health of a defined
population, such as the frail and elderly, using pro-active, preventive measures, with post-acute accountability and a view to long-term health management.

A PERS service provides a means of capturing dynamic changes in high risk patients in the period after hospital discharge to allow pro-active, preventive intervention and minimize risk of hospitalization for acute treatment [2]. A PERS service provides patients with immediate access to assistance by alerting a loved-one, caregiver or emergency medical services in the case of an incident, such as a fall, respiratory problems, chest pain or other [3]. The PERS service used in this study consists of a call button worn by a subscriber on the wrist or as a pendant, activating an intercom system in the home when pressed, and putting the subscriber in direct contact with a response agent at a dedicated call-center [4]. The service tracks types and outcomes of incidents, such as falls, whether responder assistance is needed, and ambulance transport to the hospital. Such information is critical for predicting risk of future emergency hospital transportation and for determining if intervention by means of, for instance, a frail and elderly program [5] is warranted.

The objective of this study was to develop a robust predictive model of ambulance transport to the hospital emergency department, a growing driver of costly hospital admissions [6].

Methods

Source of Data
This predictive modeling study was performed on retrospective de-identified data sets of subscribers who were enrolled in a commercial PERS service (Philips Lifeline, Framingham, MA, USA) and had an active subscription on Jan. 1st, 2014. Subscribers between the ages of 18 and 100 were included in the analyses. For all subscribers, up to one year of de-identified retrospective data on subscribers’ interactions with the PERS call-center were collected. This study was approved by the Internal Committee on Biomedical Experiments of Philips Research.

Predictive Modeling
We developed a model to predict an emergency hospital transport within 30 days (i.e., before or on Jan 31st, 2014) for the cohort of subscribers active on Jan 1st, 2014. The model was developed on data from 551,127 subscribers using generalized logistic regression with 10-fold cross-validation. Variables that were evaluated for inclusion in the predictive model of emergency hospital transport within 30 days included: subscriber demographics, self-reported medical conditions, type of subscription (i.e., private subscription, subscription through a home care program, or subscription through a government subsidized program), information about the caregiver network, and various features defined based on the points of contact of the subscriber with the call-center. These variables included the types, frequency and outcome of prior incidents and accidental calls.
For each type of incident the time since the most recent prior interaction with the call-center was analyzed for inclusion into the final predictive model. Backward variable elimination with a significance level of 0.05 for variable retention was used to develop a parsimonious logistic regression model. The primary analytic measure used to assess model performance was the auROC in the validation cohorts [7]. Furthermore, calibration across percentiles of risk was used, similar to the method in [8]. In this method, the subscribers in the validation set were divided into 100 subgroups of approximately equal size according to predicted risk, and within each subgroup the actual percentage of subscribers having at least one transport in the 30-day window was derived.

An extensive analysis was performed by exploring a variety of the modeling techniques, by changing the prediction window, by limiting the retrospective data used in model training, and by investigating seasonal effects when applying the predictive model at different periods throughout the year.

**Results**

**Summary Statistics**

From 551,127 subscribers, 13,072 (2.37%) subscribers had at least one hospital transport within 30 days of the baseline prediction date (Table 1).

| Table 1. Overview of data used for predictive model development. a: p<0.001 |
|-----------------|-----------------|-----------------|
| **Category**    | **Variable**    | **Without hospital transport in next 30 days** | **With hospital transport in next 30 days** |
| **Demographics** | # of subscribers | 538,055         | 13,072 (2.37%) |
|                 | Age at enrollment | 78 ± 12         | 75 ± 13 a |
|                 | Gender (% male)  | 18%             | 21% a |
|                 | >1 responder     | 65%             | 52% a |
| **Self-reported medical conditions** | Heart failure | 4.2% | 6.3% a |
|                 | Diabetes        | 18%             | 25% a |
|                 | COPD            | 4.8%            | 8.6% a |
| **Average # of incidents in past 90 days** | Any | 0.20 | 1.18 a |
|             | Fall            | 0.08            | 0.39 a |
|             | With EMS assistance | 0.05        | 0.33 a |
|             | With ER transport | 0.03         | 0.21 a |

**Predictive Model**

Features based on the Lifeline PERS service were derived from a total of 25.1 million rows of data. A total of 32 variables out of more than 50 potential features were retained in the final predictive model of emergency hospital transport after application of backward variable elimination.

Although interpretation of the odds ratios in a multivariate model is difficult, the following observations were made. A non-linear relation between age and outcome
was modeled by including a 2nd degree polynomial of age in the logistic regression model. A possible explanation is that the reasons for subscribing to a Medical Alert Service are different for different age groups. In relatively younger subscribers, the proportion of individuals who subscribe due to specific underlying medical conditions may be larger than in the older cohorts. While the majority of PERS subscribers are female, male gender was found a significant predictor for emergency transport. A plausible explanation is that older males who do use a PERS service could comprise a particularly vulnerable subset of the male population. Subscribers with self-reported COPD, diabetes, or heart condition were found to be at significantly increased risk. Subscribers in a home care program are often recently discharged from the hospital and they were found to be at higher risk for emergency hospital transport. During enrollment, subscribers may list contact information for several general and emergency responders. We found that subscribers with access to multiple general responders were at decreased risk for hospital transport, while subscribers listing multiple emergency responders were predicted to be at increased risk. Frequent prior hospital transports, in particular recent ones, were predictors for increased risk of future hospital transport. The frequency of other types of incidents, including falls and respiratory issues, was also predictive of future hospital transport.

The final predictive model of emergency hospital transport in 30 days resulted in \( \text{auROC} = 0.75 \pm 0.01 \) in the validation folds (Figure 1). The calibration across percentiles of risk showed that in the top percentile, the Positive Predictive Value (PPV) was 25%, i.e. in this percentile 25% of subscribers experienced an emergency transport in the next 30 days. Using a cut-off corresponding to the 1% high risk subscribers, the PPV is 10.7 times higher than the baseline risk and the false positive rate is 0.8%.

**Figure 1.** Predictive model performance evaluated by receiver operator characteristic (ROC) curve and calibration across percentiles of risk in one of the 10 validation folds. Area under the ROC curve was 0.75; PPV in the top percentile of risk was 25%.
**Use of retrospective data**

To determine the decrease in accuracy of the model in case less data would be available, logistic regression models were also trained on a truncated data set using up to 90 days of data as well as on enrollment data only, i.e. discarding features that could only be collected during a period on the PERS service (Table 2).

<table>
<thead>
<tr>
<th>Enrollment data</th>
<th>Medical alert pattern data</th>
<th>Predictive models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>No</td>
<td>Logistic regression 0.749 [0.745-0.754] 25.5% [0.244-0.265]</td>
</tr>
<tr>
<td>Yes</td>
<td>Up to 90 days</td>
<td>Neural Network 0.748 [0.743-0.752] 25.8% [0.247-0.268]</td>
</tr>
<tr>
<td>Yes</td>
<td>Up to 2 years</td>
<td>Boosted Regression Trees 0.751 [0.746-0.756] 26.4% [0.257-0.272]</td>
</tr>
</tbody>
</table>

**Modeling Techniques**

To investigate the influence of modeling technique, we additionally developed models using Neural Networks (NN) and Boosted Regression Trees (BRT). The NN models contained logistic output units and had a hidden layer with 10 nodes. The BRT models were allowed to have up to 4-way interactions between variables. The comparison (Table 3) was performed using up to one year of retrospective medical alert pattern data.

**Prediction Window Size**

Initially, a prediction period of 30 days was chosen based on a combination of operational insights and modeling requirements. On one hand, the period seemed to be sufficiently short to justify applying a preventive intervention based on the risk prediction. On the other hand the 30 day period was sufficiently large to capture a sufficient amount of events necessary for predictive modeling. To evaluate the effect of extending the prediction window, we generated models for windows of 30, 60, 90, 180 and 365 days (Figure 2). It can be seen that the auROC decreases slightly with increased prediction window size, namely from 0.75 for a window of 30 days to 0.71 for a window of 365 days. On the other hand, PPV in the top percentile of predicted risk increases from 25% for a window of 30 days to 73% for a window of 365 days. This is due to the increased prevalence with increasing the prediction window (2.4% for a 30-day window vs. 16.8% for a 365-day window).

**Table 2.** Performance for the models using 0, 90 or 365 days of retrospective medical alert data. 95% confidence intervals are given for auROC. PPV was determined in the top 1% of predicted high risk subscribers.

**Table 3.** Performance of different types of predictive models [95% confidence interval].

**Figure 2.** Predictive model performance as a function of prediction window size, evaluated by area under receiver operator characteristic (ROC) curve and PPV in the top percentile of predicted risk.
Seasonal Effects
To investigate the presence of seasonal effects, we incorporated 30-day prediction windows at each 1st day of the month over the course of 2014. To limit data processing, up to 90 days of retrospective medical alert data was used for each patient. The final processed data set for prediction included more than 8.4 million rows. We noticed that the outcome was constant across the year, with the exception of December 2014, where it was slightly higher (Figure 3).

Figure 3. Percentage of subscribers with emergency hospital transport in 30 days, starting from the 1st of each month in 2014.

The month of prediction was included as a factor in the model. The auROC was $0.713 \pm 0.003$ and the PPV in the top percentile was $24.0 \pm 0.8\%$. This was not significantly different from the performance of the 90 days model trained using Jan 1st, 2014 as the prediction date.

Subscribers Without Prior Medical Alerts
Of all subscribers active on Jan 1st, 2014, 73\% did not have any incidents in the past year. As the predictive model is mainly based on parameters related to prior incidents, one might ask what the chances are of a false negative in this group. Subscribers without incidents are mainly in the lower percentiles of predicted risk, while subscribers with prior incidents fall into higher risk percentiles (Figure 4). Of subscribers without any incidents in the past year, only 1.2\% required an emergency transport (as compared to 5.5\% in the group with one or more prior
incidents). Therefore, the risk for a false negative in subscribers without prior incidents is at most 1.2%.

**Figure 4.** Number of subscribers per predicted risk percentile, grouped by whether or not the subscriber had one or more incidents in the past year.

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**Discussion**

We developed a predictive model of risk for emergency hospital transport using PERS medical alert pattern data. The model showed good predictive performance in 10-fold cross validation (auROC = 0.75). The positive predictive value in the top 1% of predicted high risk subscribers was 25%.

Only 2.4% of subscribers experienced an emergency hospital transport in the 30-day window. Developing algorithms to predict such rare events requires a large data set to achieve sufficient events per predictor [9]. To reach optimal predictive performance, the final model contained over 30 variables, a number that exceeds human processing capacity but is relatively simple for a computer to analyze in case of a multivariate logistic regression model. Prevalence also affects the PPV of a predictive model [10]. This means that the same predictive model might have a greater PPV in certain at-risk populations, such as frail elderly, or patients recently discharged from hospital.

The predictive modeling approach has various limitations. First, the model predicts emergency hospital transports, not hospital admissions. In 2009–2010, 36.5% of emergency department visits made by persons aged 65 and over resulted in hospital admission [11]. Second, whereas epidemiological studies seek to quantify the (causal) relationship between specific variables and outcomes, the focus of predictive modeling research is on model accuracy. Therefore, inclusion of correlated predictor variables was allowed. However, this complicates interpretation of the odds ratios. Furthermore, the data set was highly imbalanced with only 2.4% in the positive class. Balancing the data may have improved the models, although this is uncertain for logistic regression models [12].

The intention is to implement these models for automatic, continuous calculation. We are also planning prospective validation studies to determine the value of the predictive model in assisting HCOs with planning early interventions to avoid
emergency department visits and subsequent hospitalizations. Model derived risk scores may be incorporated into future clinical information systems and care giver portals.

**Conclusion**

Medical alert pattern data from a PERS service can be used to predict risk for emergency hospital transport within 30 days of the time of prediction with an auROC of 0.75. The prediction model already generates useful insights in subscribers risk when only three months of PERS service data is available.

**Conflicts of Interest**

Jorn op den Buijs, Tine Smits, Marten Pijl, Mariana Simons and Linda Schertzer are employed by Royal Philips.

**Abbreviations**

auROC: area under the Receiver Operator Characteristic curve  
BRT: Boosted Regression Trees  
HCO: Healthcare organization  
NN: Neural Networks  
PERS: personal emergency response system  
PPV: positive predictive value

**References**