Predicting Hospital Admissions and Emergency Room Visits using Remote Home Monitoring Data

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***Abstract*— The costs of lengthy hospital admissions (HA) and multiple emergency room visits (ER Visits) from patients with conditions such as heart failure (HF) and chronic obstructive pulmonary disease (COPD) can place a significant burden on healthcare systems. Understanding the various factors contributing to hospitalization and ER visits could aid cost-effective management in the delivery of services leading to potential improvement on quality of life for patients. This can be facilitated by collecting data using remoting patient monitoring (RPM) services and using analytics to discover important factors about patients.**

This paper presents our research that utilizes predictive modeling to determine key factors that are significant determinant to hospitalization and multiple ER Visits. The results shows that gender, past medical history and vital status are key factors to hospital admissions and ER Visits. Additionally, when a factor to indicate the period before, during and after an ER Visits was included, the resulting model shows a very high likelihood ratio and improved p values on all vital status. Our results shows that more research is needed to fully understand the temporal patterns among variables during hospitalization or ER visit.

I. Introduction

The National Ambulatory Care Reporting System (NACRS), in Canada shows that in 2014-15 the leading conditions for which patients were admitted from EDs were Chronic Obstructive Pulmonary Disease (COPD), heart failure (HF) and pneumonia. The time spent until decision to admit for these conditions ranged from 11.2 to 11.7 hours and the additional time waiting for an inpatient bed ranged from 27.5 to 30.2 hours [1]. As a result, COPD and HF patients place a heavy burden on emergency rooms (ERs) and other areas within the hospital when they need to be admitted. Providing new approaches such as those enabled by RPM have great potential to detect changes in pathophysiology earlier. However, new knowledge for pathophysiologies that are associated with higher probability of an ER visit or hospital admission is needed to better understand trajectories of changed health status to enable new community based interventions that may reduce ER visits and hospital admissions.

Gorst et al performed a systematic review assessing levels of uptake of home telehealth by patients with HF and COPD and the factors that determine whether patients do or do not accept and continue to use telehealth. They determined that among the most frequently reported benefits of telehealth was that patients think telehealth enables them to better manage their health, by giving them better physiological control. They also note that telehealth also increases patient health knowledge, as it gives them a better understanding of their medical condition(s) [2] . However, this cohort still represent a significant number of ER visits and hospital admissions. This highlights that while there is some knowledge of risk factors leading to ER visits and hospital admission, there is great potential to empower those with these chronic conditions with more information of risk factors that lead to a greater probability of ER visits and hospital admission through new prediction models. In addition, there is great potential for new community based interventions that may reduce ER visits and hospital admissions.

Alayacare, a software company for community care providers and We Care, a division of CBI Health Group Canada's largest provider of rehabilitation and home health services, began working together in 2013 with a goal of producing an innovative approach for adverse events reduction that lead to ER visits and hospital admissions [3]. In 2015, they commenced a collaborative research project with Southlake Regional Health Centre and Health Informatics Research at the University of Ontario Institute of Technology for a RPM research study with the focus on deriving the factors that are key determinants to lengthy hospitalization and multiple ER visits. One of the goals of that research was to apply new risk score prediction models by applying predictive analytics of subsequent hospitalization and ER visits at Southlake Regional Health Centre and their regional partners using information collected from participants enrolled in the RPM study.

This paper presents results of our initial analysis for the prediction of hospital admissions and ER visits for participants enrolled in our remote patient monitoring study. Participants were referred from the Cardiac Clinic of Southlake Regional Health Centre and were referred to WeCare for home based monitoring using the Alayacare software.

The rest of the paper is organized as follows; Section II provides the literature review, Section III discusses the research results, Section IV provides a summary discussion and then concludes on Section V.

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II. LITERATURE REVIEW

In [4] we presented related research reporting on the impact of gender and medical history on ER visits and hospital admissions from this same study population. In that work we found that men were more likely to have hospital admissions compare to women and that the probability of presence of past medical history was statistical significant for seniors age 65 and over.

As noted in Gorst et al, an increase in incidences of HF and COPD are associated with an aging population. As a result, there is an increase in multiple emergency room visits and hospitalization in the elderly. This normally leads to increasing costs for care of such patients when in hospitals and therefore a more cost-effective model could be realized with services like telehealth [5]. Data collected from patients using RPM program can facilitate better understanding of patients needing care and factors that contribute to hospitalization and ER visits. To facilitate this, this paper presents results on which these factors are strong indicators of hospitalization and emergency room visits using Bayesian predictive modelling.

III. METHODS

Research ethics board approval for this research was received from both Southlake Regional Health Centre (SRHC REB #0087-1516) and the University of Ontario Institute of Technology (UOIT REB #14136) for the research study entitled "Reducing Hospital Admissions and Emergency Depoartment Visits for Chronically Ill Patients using Remote Patient Monitoring and TeleHealth Tools".

A stepwise Bayesian predictive modelling approach is adopted in this paper to determine the factors contributing to hospital admissions and multiple ER visits.

Given H as a hospital admission event and a set V comprised of variables {p1, p2, ….pn} as predictors, such that utilizing the data available i.e. age, gender, p1 = age, p2 = gender, and pn as the last available variable. Bayesian predictive modelling looks to determine the probability of an event H given a set of predictors in V, see equation (1), similar approach was adopted on predicting the ER visits.

$$\left(P(H|V) = \frac{P(V|H).P(H)}{P(V)}\right) \tag{1}$$

Where $P(H|V)$ is the probability of event H given the observed events in V, $P(V|H)$ is the probability of observing events in V, $P(V|H)/\ P(V)$ is the impact of events V on the probability of event H and $P(H)$ is the prior probability of event H, $P(V)$ is the model evidence and includes set of all hypothesis considered in prediction on event H given V.

To ensure the appropriate input variables were included in modelling, data cleaning, standardization and linkage was completed and deriving new variables as needed.

IV. RESULTS

This section provides the results generated in a stepwise approach, Section A provides results of predicting hospital admissions while section B shows the results on predicting ER visits.

A. *Predictive Modelling on Hospital Admissions*

1) *Predictive modelling on HA based on gender.*

The first model assessed gender as a predictor for hospital admissions. The models likelihood ratio was (p=0.034) indicating this model fits significantly, the Score (P=0.0154) and Wald tests (p=0.0193) indicates that hospitalization is not by chance. Male clients are 3.5 times more likely to be hospitalized compared to female clients.

2) *Bayesian Modelling: Hospital Admissions by Medical History and Gender*

The next level of prediction included medical history data building on the earlier correlation analysis reported in [4], showing there was variation of correlation on clients medical history by gender between those with and without hospital admissions. In this model, past medical history, current medical history and allergies were added to gender. The results shows a better model with a much lower likelihood ratio (p=0.0034) which indicates this model fits significantly and the statistical tests (score and wald) indicated the model is statistically significant, see details in Fig 1. This model indicates that gender (p=0.0173) and past medical history (p=0.0052) are statistically significant and indicates a strong relationship to hospitalization. There is no evidence on hospitalization based on current medical history (p=0.3641) or allergies (p=0.3152). The models odd ratio indicates that male clients are 4.5 times more likely to get hospitalization compared to females and those with lower weight get more hospitalization.

Fig 1: Predictions on hospital admissions using patient medical history and gender

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	15.7292	4	0.0034
Score	16.0550	4	0.0029
Wald	12.5835	4	0.0135

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	1.5106	0.6478	5.4367	0.0197
gender	F	1	0.7496	0.3148	5.6688	0.0173
PastMedHist_Rank		1	-0.4185	0.1498	7.8009	0.0052
CurrMedHist_Rank		1	0.1839	0.2026	0.8237	0.3641
Allergy_Rank		1	-0.1677	0.1669	1.0087	0.3152

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
gender F vs M	4.478	1.304	15.385
PastMedHist_Rank	0.658	0.491	0.883
CurrMedHist_Rank	1.202	0.808	1.788
Allergy_Rank	0.846	0.610	1.173

3) *Bayesian Modeling: Hospitalization by Age*

The next predictive model was to understand if age had any relationship to hospitalization. The mode results shows the p-values on all ages groups had no statistical significant at 0.05 level. On overall group, there is no statistical evidence that age has an effect at hospitalization (p=0.8440), likelihood ratio (p=0.6250), Score (p=0.7164) and Wald at (p=0.8440). Table 1. provides the breakdown on the p values on hospitalization per age category which all have no statistical evidence

Table 1. Maximum likelihood estimates by Age.

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	3.6338	44.1637	0.0068	0.9344
Age_GroupB	19 Below	1	8.2594	176.7	0.0022	0.9627
Age_GroupB	20 - 64	1	-1.5544	44.1663	0.0012	0.9719
Age_GroupB	65 - 74	1	-2.2901	44.1651	0.0027	0.9586
Age_GroupB	75 - 84	1	-1.9598	44.1664	0.0020	0.9646

4) *Bayesian Modelling: Hospitalization by Vital Status*

Assessment of the correlation of vital sign status and hospital admissions was then performed. The model results are shown in Fig 2, and this is a statistically significant model showing that adding vital status strongly improves the predictive model completed previously (Fig 1). Fig 2 shows there is significant impact on average weight to hospital admissions ($p<0.0001$). However, no statistical evidence that average pulse and average spo2 have any relationship to the possibility of admissions. Men are 13 times more likely to be hospitalized compared to women and a 1 factor decrease in weight, pulse to SPo2 has increase in potential hospitalization.

Fig 2: Model results on prediction of hospital admissions by gender, average: weight, pulse and spo2

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	1159.4697	5	<.0001
Score	948.7821	5	<.0001
Wald	761.3477	5	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	-2.6414	0.1852	203.4091	<.0001
gender	F	1	1.2815	0.0552	539.7039	<.0001
PastMedHist_Rank		1	-0.2939	0.0230	163.0795	<.0001
ave_weight		1	0.0591	0.00256	531.0629	<.0001
ave_pulse		1	-0.00047	0.000272	2.9422	0.0863
ave_spo2		1	2.053E-7	0.000126	0.0000	0.9987

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
gender F vs M	12.975	10.452	16.107
PastMedHist_Rank	0.745	0.712	0.780
ave_weight	1.061	1.056	1.066
ave_pulse	1.000	0.999	1.000
ave_spo2	1.000	1.000	1.000

B. *Bayesian Modelling: Emergency Room Visits*

The data shows there are clients with multiple ER visits and to understand the contributors to the multiple visits, two techniques are utilized in the modelling phase.

1) *Prediction of Emergency Room Visits.*

The first approach uses similar principles to determine if vital status, gender, and clients history are determinant on emergency room visits as was taken in modelling for hospital admissions. The resulting model results shown in Fig 3 indicates a statistically significant model with likelihood ratio, Score and Wald tests at ($p<0.0001$). Different evidence is seen compared to the model in Fig.2; there is a significant impact to readmission by all factors: gender, past medical history, average weight, average pulse, and average spo2. Men are 2 times more likely to get multiple ER Visits compared to women.

Fig 3. Model results on prediction of emergency room visits by gender, average: weight, pulse and spo2

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	320.3733	5	<.0001
Score	247.8293	5	<.0001
Wald	237.0033	5	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	0.9218	0.5707	2.6088	0.1063
gender	F	1	0.3602	0.0887	16.4970	<.0001
PastMedHist_Rank		1	0.2869	0.0385	55.5790	<.0001
ave_weight		1	-0.0346	0.00353	95.6132	<.0001
ave_pulse		1	0.0125	0.00578	4.6606	0.0309
ave_spo2		1	-0.00077	0.000369	4.3586	0.0368

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
gender F vs M	2.055	1.452	2.910
PastMedHist_Rank	1.332	1.235	1.437
ave_weight	0.966	0.959	0.973
ave_pulse	1.013	1.001	1.024
ave_spo2	0.999	0.999	1.000

2) *Prediction of Emergency Room Visits using Pre and Post ER Visit Factor.*

In this model a new variable (ERFlagPrePost) is introduced to identify if a vital status was taken during the 5 days before, during or after an emergency room visit, results shows are shown in Fig 4.

This model, demonstrates higher odds of having an ER visit with males 6 times more likely to get multiple ER visits compared to females. Additionally, the ave_pulse becomes a statistically significant factor at ($p< 0.001$) while ave_spo2 also improved to much lower p value (0.0368 to 0.0029). This model demonstrates the altered behavior of these variables around the time of ER visits with a higher likelihood ratio even though the ERFlagPrePost is seen as not significant.

Fig 4. Prediction of ER Visits using pre and post visit Factor

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	1382.4883	6	<.0001
Score	1165.3064	6	<.0001
Wald	780.1388	6	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	-9.9071	92.0272	0.0116	0.9143
gender	F	1	0.9460	0.0380	619.0544	<.0001
PastMedHist_Rank		1	-0.1040	0.0169	37.6361	<.0001
ave_weight		1	0.0276	0.00174	250.6960	<.0001
ave_pulse		1	-0.0370	0.00238	241.3810	<.0001
ave_spo2		1	0.0309	0.0104	8.8936	0.0029
ERFlagPrePost	0	1	8.0390	92.0214	0.0076	0.9304

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
gender F vs M	6.632	5.714	7.698
PastMedHist_Rank	0.901	0.872	0.932
ave_weight	1.028	1.024	1.031
ave_pulse	0.964	0.959	0.968
ave_spo2	1.031	1.011	1.053
ERFlagPrePost 0 vs 1	>999.999	<0.001	>999.999

V. DISCUSSION

Several models are presented in this paper, the initial model assessed how well gender determines hospitalization. The results shows evidence gender is statistically significant in this population and context and a strong determinant to hospital admissions. This is quite a difference to the same model using age as key predictor, the results in Table 1 indicates no statistical evidence exists to show that age contributes to client hospitalization.

As aggregation of clients medical history was performed to get a unified factor for modelling, results indicate that past medical history are a significant factor to hospitalization. Further review of actual medical history details is required. This can be facilitated using ICD coding, as noted in [6], as the method of counting diagnosis is important to understanding the real disease impact to hospitalization.

On modelling using gender, vital status and past medical history to predict the potential for hospitalization, there is a difference on factors contributing to hospitalization or ER visits. SPo2 and Pulse are seen as significant contributors to ER visits but not significant to Hospital admissions.

To further understand why pulse and SpO_2 behaviour in the time preceeding ER visits is significant, which was not the case in hospital admissions, a correlation analysis was performed on vital status by gender. A strong correlation to ER Visits on average weight, average pules and average SpO_2 on female clients ($p<0.001$) was apparent. However this was different from male clients where correlation to ER visits is seen on average weight and average pulse ($p<0.001$) while no correlation of average SpO_2 ($p=0.559$). Further research was required on vital status leading to an ER visit compared to actual hospitalization.

To address this, a new model was developed by adding a factor to indicate if a vital status is 5 days before, during or after an ER Visit. The results in Fig 4 shows higher odds of multiple ER visits for male clients compared to females and a statistical significant impact on ave_pulse and ave_SPo2 compared to other models. Although the ERFlagPrePost doesn't appear to be a statistically significant factor, further analysis is required to understand the patterns preceeding, during and after an ER visit. This can be facilitated using temporal abstraction and pattern recognition models.

McGregor has patented a temporal data mining method known as the Service-Based Multi-Dimensional Temporal Data Mining ($STDM^n_0$) [7]. Inibhunu and McGregor have proposed extensions to that research to add components for data reduction, generation of temporal abstraction and discovery of relationships and patterns in the abstracted data and then mining frequently occurring patterns [8].

In future work we will be including temporal abstraction and deriving temporal patterns as input for frequent pattern mining algorithms to understand the underlying temporal relationships on vital status in data collected from patients participating in RPM program in combination with other data sets in order to get a complete patient flow. Our premise is that this discovery will highlight why some factors are high determinants of hospital admissions and multiple ER Visits.

VI. CONCLUSION

This research provides our work on mining data collected from RPM program, the goal is to understand and quantify the contributing factors to HA and multiple ER visits. The premise of this research is that identification of such factors could aid in making decisions on care of patients and potential reduction of costs associated with hospitalization leading. We have taken a phased approach to mining client data and we expect more complex models as project continues.

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