Health Informatics Meets eHealth
G. Schreier et al. (Eds.)

doi:10.3233/978-1-61499-645-3-25

Analyzing Readmissions Patterns: Assessment of the LACE Tool Impact

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Abstract. This paper will discuss the assessment of the use of the LACE tool at North York General Hospital (NYGH). The LACE tool estimates the readmission risk of patients. This paper describes the tool and a modified LACE score implementation and use at NYGH. We also describe our statistical analysis for the LACE effectiveness in order to inform future decisions in resource allocations. We will look at suggestions for adjustments in the way the LACE tool is used as well as implications for service delivery and patients' quality of life. Our study shows that the modified LACE is a predictive tool for readmission risk in day-to-day hospital activity, but that implementation of LACE alone cannot reduce readmission rates unless coupled with efforts of those in charge of providing community-based care.

Keywords. LACE, Readmission, Health Management, Quality of Care, Quality of Service, Clinical IT, Discharge Summary, Discharge.

1. Introduction

In Canada, one in 12 patients is readmitted within 30 days of discharge. In Ontario, 9% of acute care patients returned to the emergency room and one sixth of them returned more than once within seven days of initial discharge [1]. Inpatient readmissions account for more than one in 10 dollars spent on inpatient care in Canada (excluding physician fees for services). Costs are greatest for **medical patients** who account for 64.9% of unplanned readmissions followed by **surgical** patients at 23.9% [2].

Hospital 30-days readmissions are largely unplanned and preventable. The rates of readmission are highest for clients with congestive heart failure, myocardial infarction, and pneumonia - respectively [3]. Vascular surgeries are also associated with high rates of readmission within 30 days. Research suggests that the reasons behind readmission within 30 days of discharge have to do with both the **patient characteristics** and the characteristics of the **procedure** (e.g. a 75-year-old client with diabetes was more likely to be readmitted to the hospital following an invasive vascular surgery compared to younger patients with no chronic disease [4]).

Between 2010 and 2013, the Medicine program at North York General Hospital (NYGH), Toronto, Canada, has seen an increasing trend in its 30-day readmission rate. During that period, NYGH was in excess of the corporate target for readmissions (set at 7.3%) [5]. In an effort to reduce readmissions, NYGH undertook an initiative in June 2013 to implement a risk assessment tool called LACE. LACE is "an index to predict early death or unplanned readmission after discharge from hospital to the community"

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[8] that is calculated based on: **L**ength of stay ("L"), **A**cuity of the admission ("A"), patient **C**omorbidity ("C"), and **E**mergency department number of visits ("E") that was developed by van Walraven et al. [6-9].

This project analyzed readmission data from NYGH to gain insight into LACE and inform future resource allocation decisions. The research project also has the potential to impact patients' quality of life since use of the LACE tool is designed for early identification of patients who are high risk for readmission and thus to start the discharge planning with the inter-professional team, in an attempt to reduce readmission rate.

NYGH is intending to dispatch new resources (e.g. teaching packs) to this project, and has already invested initiatives in order to follow up patients having a LACE score greater or equal to 10. Nevertheless, for a wise use of current and future resources, it was critical to analyze the re-admission patterns at NYGH and investigate if LACE is working as predicted or if it needs adjustment to fit NYGH patient population.

2. Methods

LACE implementation at NYGH. Before starting any data analysis, we had to understand how NYGH implemented the LACE tool in practice. In 2010, when Walraven and his colleagues developed the 'LACE' tool[8], they defined L as the current length of stay in the hospital (i.e. LOS for the index admission). Largely for practical reasons, particularly the need to use the LACE score to plan in advance of discharge, NYGH has defined L as patients' length of stay in his/her previous acute care visit within the last 30 days. The Acuity of the Admission weight indicates if the current admission is acute or not and NYGH calculated this in the same manner as Walraven et al. Comorbidity of the patient is measured by using the Charlson comorbidity index score in the original LACE work, though NYGH modified the scale used by the original authors of LACE by giving a weight of 6 instead of 5 for metastatic cancer. Using Walraven's approach, 'Emergency department use' is measured by looking at patients' total number of visits to the emergency department in the six months immediately prior to the index admission. The 'L', 'A', and 'E' and C components of LACE are calculated manually by the nurse on the floor during the index admission and are entered in the LACE software. Overall, a patient with a LACE score <10 is considered to at low risk of readmission while LACE >=10 suggests a high risk of readmission. The following figure summarizes LACE scoring methodology as has been used by NYGH staff.

Procedure for Calculating LACE. Lace was implemented at NYGH between June and October 2013 on a number of medicine units in the hospital. For each admitted patient a nurse uses a software to enter the four components of the LACE score manually, the software then calculates a LACE score for the patient. In addition to obtaining one year of LACE data (June 2013 – June 2014), we accessed data on readmission rates for each LACE unit dating back one year prior to LACE implementation at the hospital thereby allowing us to look at readmission rates in the one-year period leading up and one year following LACE implementation.

Analysis. Data were received in Excel™; then it was cleaned, imported and analyzed into SPSS™. Ethics approval was obtained from the Ethical Review Board at NYGH. In addition, each researcher completed the "Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans Course on Research Ethics" certificate (TCPS2: core).

Attribute	Value	Points	Score
Length of Stay (Prior Admit)	Less 1 day	0	
	1 day	1	
	2 days	2	
	3 days	3	
	4-6 days	4	
	7-13 days	5	
	14 or more days	6	
Acute Admission	Inpatient	3	
	Observation	0	
Comorbidity (Cumulative to a max of 6 pts)	No prior history	0	
	DM no complications, Cerebrovascular disease, Hx of MI, PVD, PUD	1	
	Mild liver disease, DM with end organ damage, CHF, COPD, Cancer, Leukemia, Lymphoma, any tumor, moderate to severe renal disease	2	
	Dementia or connective tissue disease	3	
	Moderate or severe liver disease or HIV infection	4	
	Metastatic cancer	6	
Emergency room visits during previous 6 months	0 visits	0	
	1 visits	1	
	2 visits	2	
	3 visits	3	
	4 or more visits	4	
	Take the sum of the points and enter the total → ***If LACE score is 11 or greater, CM to send tool to agency/facility patient is referred to on discharge**		

Figure 1: LACE score as has been implemented by NYGH

3. Results

We have used descriptive statistics to compute the readmission rates for the low risk (LACE <10) and high risk (LACE >=10) groups and found them to be 9.7 % and 18.7%, respectively, in the one-year period following LACE implementation.

3.1. LACE predictive ability in the hospital setting

In order to conclude the predictive power of the modified LACE tool, we have conducted a logistic regression analysis that allows us to uncover and compare the odds-ratio of LACE scores greater than 10 and LACE scores lower than 10 in relation to readmission, and consequently to compare their corresponding predictive ability. The logistic regression revealed that the patients in the high risk group (LACE score ≥ 10) are **2.05** times more likely to be readmitted than those in the low risk group (LACE score < 10).

3.2. Readmission reduction

We were interested in looking into any significant difference in readmission rates for the months before LACE compared to those for the months after LACE index has been introduced. The readmission rate distribution was skewed and consequently we have used the non-parametric Mann-Whitney U test to compare readmissions rates before and after LACE implementation.

The Mann-Whitney statistical analysis showed no significant difference between the period before LACE and after LACE; consequently, LACE per say had no effect on readmission rates.

3.3. LACE threshold for risky patients

Managers at NYGH have noticed that some patients with low LACE score are being readmitted and hypothesized that a reduction in the LACE threshold to 8 would have a better discriminatory powers than 10 and allows us to capture more patients with high risk of readmission. We modified the LACE threshold to 8, in order to test whether a lower LACE score would have more predictive power. Regression results showed that for a threshold of 8 (instead of 10) LACE would have a less predictive power as the regression coefficient decreased (2.01 compared to 2.05 for threshold 10). Consequently, the LACE score threshold should be kept at 10.

3.4. Calculating LACE in the ward: data entry

Since we conducted a retrospective analysis, we were able to compute the exact 'L' and 'E' components of LACE automatically using SPSS. We compared our computed, and hence accurate, 'L' and 'E' to the manual data entered during the patients' stay in the hospital. We have conducted a Weighted Kappa Analysis to compare the agreement between the scores entered in LACE and our scores.

The data entry error rates of L and E were 33% and 49% respectively. Moreover, the level of agreement between the L and E values entered by NYGH staff compared to the correct L and E values that we have been able to compute were significantly different (Kappa values <0.7).

The data entry errors in L and E resulted in missing risky readmissions and spending time on non-risky ones. Between September 2013 and August 2014, 11% of the cases considered by the NYGH team as risky should have been considered low risk. This resulted in unnecessary resource utilization. On the other hand, between September 2013 and August 2014, 23% of patients were considered low risk while they in the high-risk range. This resulted in missing high-risk patients.

Moreover, we have conducted a logistic regression analysis that showed that our accurate LACE scores give higher odds ratio than those entered manually into NYGH system, which meant that if 'L' and 'E' were accurately entered, LACE would make a better patients' readmission prediction.

4. Conclusions

The main question was to investigate is the LACE tool is a good predictor of readmission in the real world, our data analysis shows that effectively the LACE tool is a good predictor for readmission.

The second question we had is to see if the introduction of LACE at NYGH had any influence on readmission rates; the data analysis showed that calculating LACE is not sufficient to reduce readmissions. Instead, more collaborative, cross-sectorial efforts that include those in charge of providing community-based care are needed to try to address the problem of readmissions.

As for the third question regarding the effect of any change in the LACE threshold for high risk patients (e.g. reducing the score), the data analysis showed that the threshold 10 is more appropriate than 8 and should be kept in use.

The fourth question we addressed was the accuracy of the data entry, our data analysis showed significant data entry errors which effect was to miss high risky patients and to use unnecessary resources for low risky patients. Consequently, modified approaches that reduce reliance on manual capture of LACE elements are needed. This will yield better data quality, better risk assessment and reduces data collection burden for front-line staff.

We are currently in the process of analyzing the data using Geographic Information Systems methodologies. The GIS analysis may help illuminate socio-economic and/or socio-cultural factors that may influence readmissions. We already know that geography has an impact on patient's health [10].

Finally, in our study we could not account for (remove) patients who die within 30 days of discharge, which must have introduced some bias in the data analysis.

Acknowledgment

We would like to acknowledge the "NYGH Exploration Fund" for funding our project.

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