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Evaluation of Patients at Risk of Hospital Readmission (PARR) and LACE Risk Score for New Zealand Context

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Abstract. Identification and prediction of patients who are at risk of hospital readmission is a critical step towards the reduction of the potential avoidable costs for healthcare organisations. This research was focused on the evaluation of LACE Index for Readmission - Length of stay (days), Acute (emergent) admission, Charlson Comorbidity Index and number of ED visits within six months (LACE) and Patients At Risk of Hospital Readmission (PARR) using New Zealand hospital admissions. This research estimates the risk for all readmissions rather than only those in a subset of referenced conditions. In total, 213,440 admissions between 1 Jan 2015 and 31 Dec 2016 were selected after appropriate ethics approvals and permissions from the three hospitals. The evaluation method used is the Receiver Operating Characteristics (ROC) analysis to evaluate the accuracy of both the LACE and PARR models. As a result, The LACE index achieved an Area Under the Curve (AUC) score of 0.658 in predicting 30-day readmissions. The optimal cut-off for the LACE index is a score of 7 or more with sensitivity of 0.752 and specificity of 0.564. Whereas, the PARR algorithm achieved an AUC score of 0.628 in predicting 30-day readmissions. The optimal cut-off for the PARR index is a score of 0.34 or more with sensitivity of 0.714 and specificity of 0.542.

Keywords. LACE readmission risk, patient at risk of readmission, hospitalisation, risk of readmission, validation of LACE, admissions, 30-days risk of readmission score

Introduction

Hospital readmissions is a major issue worldwide, costing healthcare organisations a significant amount of money, wastage of resources, repeat orders and significant impact on the patient's life [1-2]. It is estimated about 20% of older adults were re-hospitalised within 30 days and around 30% within a year [3-4]. Chronic conditions or long-term conditions such as heart diseases are at even higher risk of readmission. There is potential

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for a large number of these readmissions to be avoided, this is in both the patient's interest, as well as the potential to save significant amounts in healthcare spending. This raises the question of which patient groups should be targeted in order to most effectively use the resources available for preventing readmissions [4].

As a means to fiscally incentivise healthcare organisations to put in place strategies to lower this high readmission rate, in the US, penalties are imposed by the Centers for Medicare and Medicaid (CMS). The Medicare Hospital Readmissions Reduction Program (HRRP) will reduce reimbursement for thousands of hospitals in 2018. Under HRRP they will withhold millions of dollars in payments over the next year [4-7].

To identify the high-risk readmission patients, Billings et al. [8] developed the 'patients at risk of hospital readmission' (PARR) predictive risk tool, initially used by primary care clinicians to identify the high-risk patients for the next 12 months. A second tool, was subsequently developed by Pannatoni et al. [9], combining multiple data sources with general practice electronic medical records for the New Zealand population, using hospital episode statistics.

The focus of this research was to compare and evaluate the LACE Index for Readmission - Length of stay (days), Acute (emergent) admission, Charlson Comorbidity Index and number of ED visits within six months (LACE), and the New Zealand version of Patients At Risk of Hospital Readmission (PARR) using admissions data from the New Zealand hospitals.

From the literature, we found six recent studies on risk of readmission using LACE and PARR for 30-day, 60-day, unplanned, emergency, or potentially avoidable readmission. On an average, the typical c-statistic or area under the receiver operating characteristic curve (AUC) for these models found to be within a range of 0.68 to 0.75 [10-13].

1. Methodology, Data Analysis and Approach

We defined the criteria for readmission as " the d ate of an admission is within the specified number of days (e.g. 30 days) of the previous index admission discharge date". This research estimates the risk for all readmissions rather than only those in a subset of referenced conditions. Data has been taken after obtaining ethical approval from the local ethics committee - Awhina Knowledge and Research Centre, Waitemata District Health Board # RM13857.

Admission Data: Adult (>15 years of age) admissions from three hospitals in the Auckland area. In total 213,440 admissions between 1 Jan 2015 and 31 Dec 2016 were selected. Of these, 33,322 were excluded from the analysis because of death during the index admission or having a discharge destination other than home at an index discharge. Of the 180,118 admissions remaining in the study, 22,565 (12.5%) of these were readmitted in the 30 days following the discharge. Data pre-processing was carried out to understand various admission codes such as, AC (acute admission), AA (arranged admission), AP (private hospital elective admission), WN (admitted from waiting list – normal) etc. [10]. Also, the second admission must be an acute admission with the code 'AC'. The evaluation method used is the Receiver Operation Characteristic (ROC) analysis for the accuracy of both the LACE and PARR models, with the AUC score reported.

Data variables used: LACE [14]– Length of stay (days), Acute admission, number of ED visits within six months, the Charlson Comorbidity Index which includes (age,

diabetes mellitus, liver disease, solid tumor, AIDS, moderate to severe CKD, CHF, myocardial infarction, COPD, peripheral vascular disease, CVA or TIA, dementia, hemiplegia, connective tissue disease, leukemia, malignant lymphoma, peptic ulcer disease) [14] and PARR [15] – gender, age, race (Maori, Pacific, Asian, others), cost weight of last admission, code for last submission, diagnoses for last admission and number of acute admissions in the previous 90 days, 180 days and 2 years [15].

2. Comparison and Evaluation Results

2.1. LACE Evaluation

The LACE index achieved an AUC score of 0.658 in predicting 30- day readmissions. The optimal cut-off for the LACE index is a score of 7 or more with sensitivity of 0.752 and specificity of 0.564, as shown in table 1 and figure 1 shows the ROC curve for LACE with false positive vs true positive rates.

Table 1. The optimal cut-off for the LACE index.

LACE	1	2	3	4	5	6	**7**	8	9	10
AUC	0.569	0.586	0.602	0.620	0.644	0.657	**0.658**	0.633	0.607	0.591
Sensitivity	0.939	0.924	0.904	0.805	0.688	0.625	**0.564**	0.444	0.337	0.270
Specificity	0.200	0.249	0.299	0.435	0.600	0.688	**0.752**	0.823	0.878	0.913

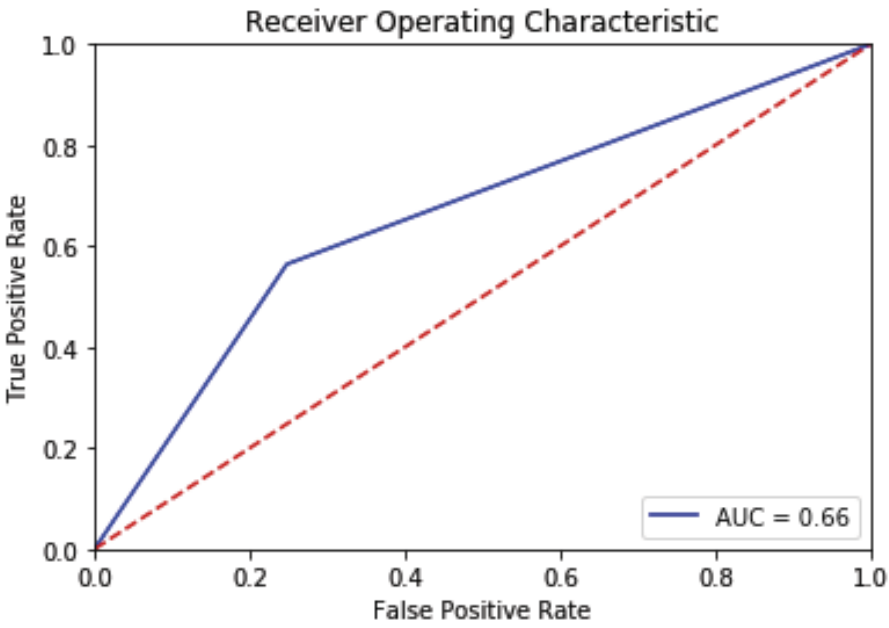

Figure 1. The ROC curve for LACE with false positive and true positive rates.

2.2. PARR Evaluation

The PARR algorithm achieved an AUC score of 0.628 in predicting 30-day readmissions as shown in Table 2. The optimal cut-off for PARR index is a score of 0.34 or more with sensitivity of 0.714 and specificity of 0.542, as shown in Table 3 and Figure 2 shows the ROC curve for PARR with false positive vs true positive rates.

Table 2. AUC score of 0.628 in predicting 30-day readmission for PARR index.

PARR	0.1	0.2	0.3	**0.4**	0.5	0.6	0.7	0.8	0.9
AUC	0.500	0.569	0.622	**0.624**	0.610	0.592	0.572	0.553	0.533
Sensitivity	0.999	0.847	0.617	**0.457**	0.345	0.262	0.190	0.131	0.078
Specificity	0.000	0.291	0.626	**0.790**	0.873	0.922	0.954	0.975	0.989

Table 3. The optimal cut-off for the PARR index.

PARR	0.31	0.32	0.33	**0.34**	0.35	0.36	0.37	0.38	0.39
AUC	0.625	0.628	0.628	**0.628**	0.628	0.627	0.626	0.625	0.624
Sensitivity	0.597	0.574	0.559	**0.542**	0.528	0.510	0.497	0.482	0.468
Specificity	0.653	0.683	0.698	**0.714**	0.729	0.744	0.756	0.769	0.780

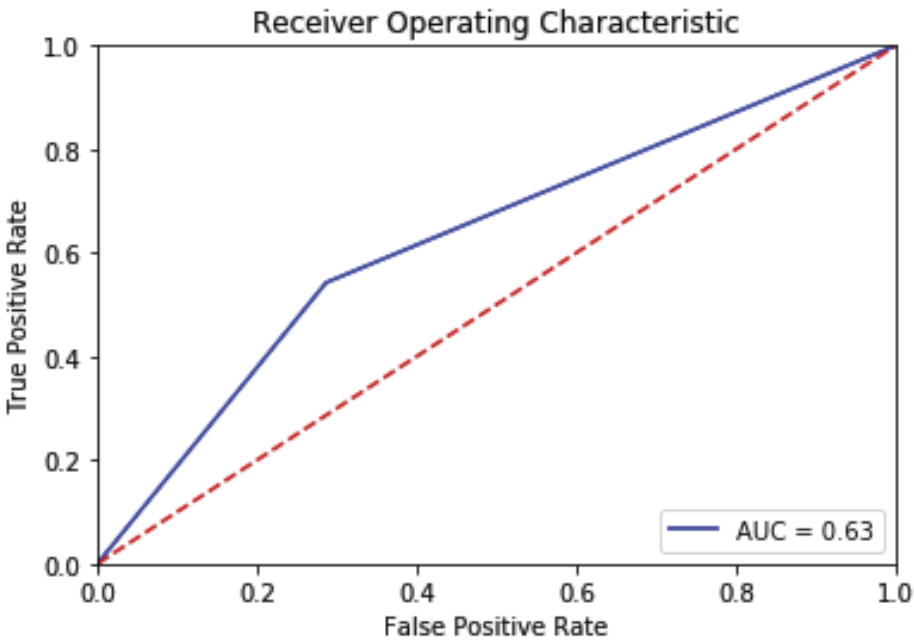

Figure 2. The ROC curve for LACE with false positive and true positive rates.

3. Conclusion and Discussion

Hospitals with high 30-day readmission rates are motivating organisations to innovate and implement better quality and safety measures. Current risk of readmission models raise concerns about the ability to standardise risk across multiple hospitals. There is a high need for risk prediction and risk adjustment models to become more accurate, and to be utilised in hospital for incentives or penalties. Current clinical estimations are often based on subjective parameters, a clinician's own experience and with limited/soiled information available at the point of care.

It is evident from the literature that current risk stratification tools lack accuracy when compared to a clinician's clinical judgment in identifying patients at increased risk of adverse events [16-17]. Independent risk stratification tools may provide clinicians with additional information to guide clinical decision-making, but further evaluation and validation is required to provide evidence of reproducible accuracy and sufficient predictive power to provide clinicians with confidence to use the results/outcomes. This study shows how ineffective the two risk of hospital readmission models (LACE and PARR) are when applied to the New Zealand population and local context. As the next steps, we will be developing a New Zealand specific risk of readmission model after reviewing the literature for effective factors apart from LACE and PARR.

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