A Model for Predicting Readmission Risk in New Zealand

Rhema Vaithianathan, Nan Jiang and Toni Ashton*

October, 2010

Abstract

Objective To develop an algorithm which predicts hospital readmission risk for New Zealand using routinely collected data. To utilise the model to develop a business case for hospital avoidance interventions.

Data Sources: Hospital episode statistics from the Waitemata District Health Board in Auckland for the three years from 01 July 2006 to 30 June 2009.

Population: All residents aged over 17 years who were admitted to a Waitemata District Health Board Hospital facility. A sample of 134,262 individuals was analysed.

Design Multivariate logistic regression analysis was used to develop the algorithm which predicts readmission to hospital in the 12 months following the date of discharge. Financial scenario modeling using the algorithm as a case-finding tool.

Results The key factors for predicting readmission were age, sex, diagnosis of last admission, length of stay and cost-weight of previous admission. The prognostic strength of the algorithm was good, with a randomly selected patient with a future re-admission being 71.18% more likely to receive a higher risk score than one who will not have a future admission.

Conclusions A method of predicting individual patients at highest risk of readmission to hospital in the 12 months following discharge shows reasonable prognostic strength. If used as the basis for targeting patients for a hospital avoidance programme, it is found to generate net savings.

* RV and NJ are at the Department of Economics and TA is at National Institute for Health Innovation, School of Population Health, University of Auckland. RV is Corresponding author r.vaithianathan@auckland.ac.nz. We acknowledge Faculty Research Grant #3623114.

What is known? Predictive Risk Models which utilize routinely collected data to develop algorithms are used in England to stratify patients according to their hospital admission risk. An individual's risk score can be used as a basis to select patients for hospital avoidance programmes.

What does this paper add? This paper uses hospital data collected by a New Zealand hospital to create a prediction alogorithms and illustrates how hospital avoidance business case can be developed using the model.

What does this add to practice? The pressures placed on health systems in both Australia and New Zealand has lead to increased interest in hospital avoidance programmes. Predictive Risk Models are a practical way to increase the efficacy of such programmes.

Introduction

In most health care systems, a small fraction of the population accounts for the bulk of health care usage costs [1-4]. In Counties Manukau District Health Board (DHB) for instance, less than one-fifth of the population account for almost half of all adult medical bed days. The highly skewed nature of utilisation and health care expenditure implies that the cost-effectiveness of "upstream interventions", such as hospital readmission avoidance programmes, will be improved if they target patients who are at sufficiently high risk of hospitalisation and identify these patients with sufficient lead time for the intervention to have an impact [5].

In response to the challenge of identifying these high risk patients, Billings et al. developed the 'patient at risk for rehospitalisation' (PARR) predictive risk modelling (PRM) tool [6]. A second tool, the Combined Predictive Risk Model, was subsequently developed [4]. These tools are reported to be used by 72% of NHS agencies in England responsible for managing chronic care in the community [7].

Pannatoni *et al.* [4] argue that a similar tool is feasible for New Zealand given that details of all public hospital admissions are routinely collected in the National Minimum Data Set (NMDS). In this paper we use this data set to develop a case finding algorithm for the Waitemata District Health Board (WDHB) to enable it to risk stratify its patient population.

The WDHB has the largest catchment of the 20 DHBs in New Zealand with more than 525,000 residents. It is located in Auckland, the largest city in New Zealand, and therefore principally serves an urban population.

Method

The methodology used in this study follows that developed by Billings et al. for the PARR case finding algorithm in England [6]. We used a subset of WDHB hospital episode data of all adult acute admissions (i.e. unplanned) over 3 years from 01 July 2006 to 30 June 2009. The sample for analysis was selected as follows. Only patients who were admitted between 01 January 2008 and 30 June 2008 were selected. For each patient, a “triggering” admission date (TAD) was identified. If patients had more than one admission during the period, the earliest admission was considered as his/her TAD.

Patients who died in the 12 months following the TAD or who were less than 17 years old at the TAD were excluded from the analysis. Patients who had more than one TAD on the same day were dropped due to our inability to ascertain the reason for this multiplicity. For each patient in the sample, we identified whether the patient had a readmission during 01 July 2008 and 30 June 2009 (see Figure 1).

For each patient, data on the patient’s previous acute hospital admissions back to 01 July 2006 were coded to determine the number of acute admissions in the previous 90, 180 and 365 days, the total number of previous acute admissions and whether or not this patient was previously admitted for a reference condition as defined by Billing et al [7]. The final sample size was 134,262 patients.

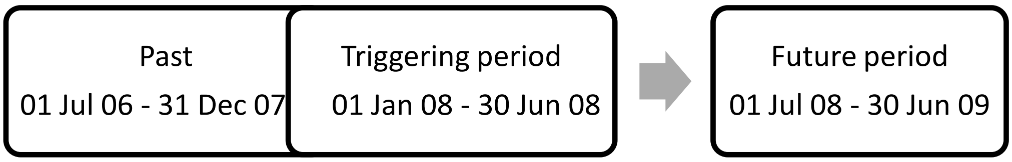

FIGURE 1: TIMING OF THE EVENTS

We constructed disease categories using DRG codes. Individual characteristics of sex, age and ethnicity are recorded within the NMDS. A step-wise multivariate statistical analysis was undertaken in order to develop an algorithm to predict patients at high risk of readmission in the 12 months following the TAD. This algorithm was developed on half the sample (N=67,131). The coefficients for the 41 most powerful variables were chosen on the basis of maximizing the log-likelihood ratio. We then applied the model to the remaining 50% of the population (N=67,131) to validate the findings of the algorithm from the first sample. All analyses were conducted using the logit command and Stata 11 (64 bits). Unlike Billings *et al.* [6], we estimate the risk *for all readmissions* rather than only those in a subset of “reference conditions”.

The predictor variables were chosen as follows. Variables which were always insignificant no matter how many other variables were included in the logistic regression were dropped. The estimated beta weights were applied to the development sample to derive the prognostic characteristics of the algorithm.[1] The variables that were included in the model

---

[1] The beta weights for the model can be obtained from the author upon request.

were functions of sex, age, ethnicity, DRG of admission, length of stay, number of admissions in past 6 months and cost-weights of previous admissions.

Results

	Risk score threshold			
	70	**80**	**90**	**99**
No. of patients flagged	2,403	1,268	526	96
Share of those flagged who are re-admitted (PPV (%))	73.37	78.08	83.46	91.67
Share of those flagged who are *not* re-admitted (1-PPV, %)	26.63	21.92	16.54	8.33
Share of re-admitted patients correctly flagged (Sensitivity (%))	8.75	4.91	2.18	0.44
Specificity (%)	98.64	99.41	99.81	99.98
Average number of re-admissions for correctly flagged patients	4.15	4.94	6.66	11.76

TABLE 12: PROGNOSTIC STRENGTH AT DIFFERENT RISK SCORE THRESHOLDS

2 reports on the ability of the algorithm to act as a basis for selecting patients for an intervention for WDHB. The Positive Predictive Value (PPV) indicates the percentage of patients who are flagged (i.e. exceed the risk-score threshold) and subsequently are admitted. The 1-PPV value, on the other hand, is critical in assessing the potential for the tool to increase the cost effectiveness of hospital readmission avoidance programmes. If 1-PPV is large, then the algorithm results in patients who are incorrectly identified and incorrectly recruited to the hospital avoidance programme. Therefore, the total savings from the initiative will be lower. This is because the potential savings derived from reducing subsequent admissions are unavailable for these patients who are incorrectly identified.

Sensitivity measures how well this case-finding mechanism performs in finding patients who are potentially in need of intervention (i.e. have a subsequent readmission). At a risk score threshold of 70, the algorithm identifies 2,403 patients, of whom 73.37% would have been correctly identified (compared with 77% in the UK Parr Tool [6]) . The rest (26.63%) would have been flagged incorrectly.

The receiver operating characteristic (ROC) curve illustrates the trade-offs between sensitivity and 1-specificity (see Figure 23). The area under the curve indicates a 71.18% probability that a randomly selected patient with a future re-admission will receive a higher risk score than a randomly selected patient who will not have a future admission. This compares favourably with the ROC curve of the UK Parr Tool which had a lower area under the ROC curve (68.5%) which suggests that the latter has a slightly worse prognostic strength – although we cannot test whether this difference is statistically significant [8].

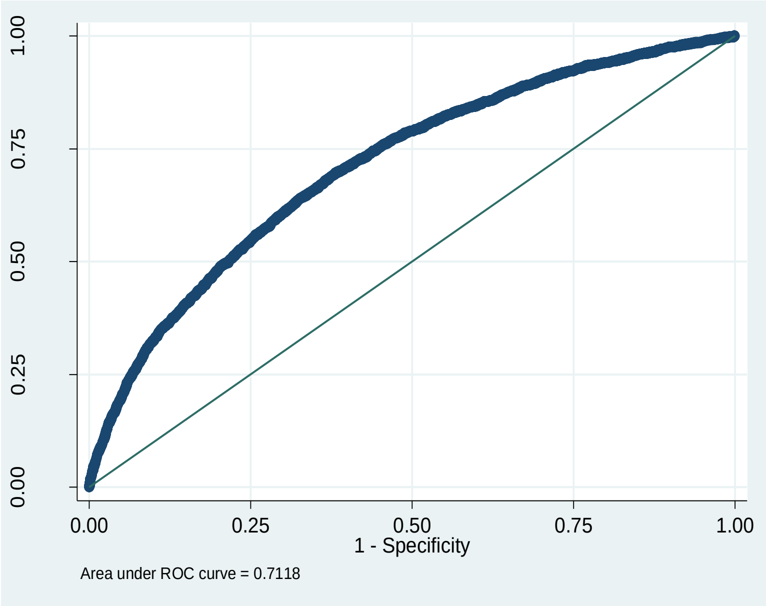

FIGURE 23: ROC CURVE FOR MODEL

Development of a Business Case

To judge the usefulness of the model, we use it to build a business case for hospital readmission avoidance programmes (See

Risk score threshold	No. admitted patients identified	No. patients flagged incorrectly (not admitted)	Total cost of intervention	Admissions within 12 months for correctly flagged patients	Intervention saving ($4756 per admission)	Net savings
Intervention cost of $500 per patient						
80	990	278	$634,000	4.94	$2,325,969	$1,691,969
90	439	87	$263,000	6.66	$1,390,531	$1,127,531
99	88	8	$48,000	11.76	$492,189	$444,189
Intervention cost of $750 per patient						
80	990	278	$951,000	4.94	$2,325,969	$1,374,969
90	439	87	$394,500	6.66	$1,390,531	$996,031
99	88	8	$72,000	11.76	$492,189	$420,189
Intervention cost of $1,000 per patient						
80	990	278	$1,268,000	4.94	$2,325,969	$1,057,969
90	439	87	$526,000	6.66	$1,390,531	$864,531
99	88	8	$96,000	11.76	$492,189	$396,189

TABLE 2). We assume three levels of intervention costs : $500, $750 and $1,000 per patient. We also assume that the intervention is effective in reducing readmission rates by 10% amongst those patients who did have a readmission. We calculate the savings from avoiding admissions on the basis of the average cost-weight per admission in our sample of discharges (using the average cost-weight multiplied by the national reference price of $4,410).

The business case estimates the net costs or savings from an intervention with a target level of efficacy and risk threshold. For example, an intervention which costs \$500 per patient and reduces hospital admission by 10% yields an expected net saving of \$444,189 if targeted at the 1% highest risk group.

Risk score threshold	No. admitted patients identified	No. patients flagged incorrectly (not admitted)	Total cost of intervention	Admissions within 12 months for correctly flagged patients	Intervention saving ($4756 per admission)	Net savings
Intervention cost of $500 per patient						
80	990	278	$634,000	4.94	$2,325,969	$1,691,969
90	439	87	$263,000	6.66	$1,390,531	$1,127,531
99	88	8	$48,000	11.76	$492,189	$444,189
Intervention cost of $750 per patient						
80	990	278	$951,000	4.94	$2,325,969	$1,374,969
90	439	87	$394,500	6.66	$1,390,531	$996,031
99	88	8	$72,000	11.76	$492,189	$420,189
Intervention cost of $1,000 per patient						
80	990	278	$1,268,000	4.94	$2,325,969	$1,057,969
90	439	87	$526,000	6.66	$1,390,531	$864,531
99	88	8	$96,000	11.76	$492,189	$396,189

TABLE 2: BUSINESS CASE FOR HOSPITAL AVOIDANCE PROGRAMME WHICH IS 10% EFFECTIVE

Discussion

The PRM we estimated achieved reasonable prognostic strength using routinely collected data for hospital admissions. Greater accuracy may be achieved if a more comprehensive data set was to be used: for example, by including outpatient data, general practice consultations and pharmacy data. However the attraction of the model presented here is that it does not require the linkage of different data sets and can therefore be run fairly readily by analysts.

An alternative approach to using a PRM such as this is to utilize a threshold model wherein patients are recruited into a hospital avoidance programme on the basis of meeting a certain number of fixed criteria. The advantage of threshold models is that they are simple to use. A disadvantage is that threshold models do not allow providers to calibrate the number of patients who are flagged [4]. In contrast, with a PRM, one may readily identify the top 1%, 0.1% or 0.01% of risk groups. Threshold models are also thought to suffer more starkly from the problems of regression to the mean in the sense that they are more inclined to identify patients that have been at high risk of readmission in the past rather than being at high risk in the future.

To explore the differences between the PRM and a threshold model, we compared this to the case finding tool used by the Frequently Admitted Medical Admissions (FAMA) programme, an intensive case management programme designed to reduce hospitalization [5]. FAMA applied criteria similar to other chronic care management programmes (such as Evercare in the UK) and flagged patients on the basis of 2 or more previous admissions in last 12 months for a total of 5 or more bed days. Patients who are no more than 15 years old and/or dead during their triggering admission are excluded. When applied to our sample, the threshold flagged 15,629 patients (11.64% of the 134,262 individuals) in our sample. Within the flagged group, 9,071 (58%) were actually readmitted in the future period.

To directly compare this method with a PRM approach we calculated the risk score that would be required to flag 15,629 patients Of the alternative 15,629 patients flagged by PRM, 9,792 (63%) of them were readmitted in the 12 months after the triggering period - which is 721 more than were flagged by FAMA.

It is also important to ask whether the PRM is a better at case-finding than clinical judgment. The argument that doctors might be better able to judge the risk of admission of a patient into hospital than a statistical algorithm requires further analysis.

Our business case was not based on any particular hospital avoidance programme. In our example, there are net savings at all risk thresholds, even though we assumed conservatively that the intervention would prevent only 10% of readmissions. Further research is required to understand what factors contribute to readmission by the particular set of patients that are flagged by the PRM, what types of interventions are effective in reducing their readmissions, and how much these interventions cost.

Our business case was developed assuming that the avoided hospital admission would cost the same as an average admission. It may be argued that the average cost of a hospital admission is higher than the marginal cost. Therefore, hospital avoidance programmes which use the average cost of avoided hospital stay over-estimate the savings in the sense that, unless a hospital is able to shut a ward and reduce staff numbers, it is unlikely that avoidance programmes will result in real savings to the health system. This is a somewhat specious argument as it fails to recognize that at some scale of hospital avoidance, the marginal cost and the average cost are the same. Indeed, it could be argued that it is this type of flawed reasoning that continues to see extremely high levels of hospital admissions which could be avoided. We therefore would argue that pricing hospital stays at their average cost is a valid approach.

Conclusion

A model for predicting individual patients at highest risk of readmission to hospital in the 12 months following discharge using data that are routinely collected in New Zealand shows reasonable prognostic strength. Our business model suggests that, when linked with an effective intervention, the use of the PRM has the potential to make substantial savings through avoided readmissions. Further research is required to compare the prognostic strength of a PRM approach with standard clinical judgment, and to examine the impact that using a PRM to identify at-risk patients can have on the cost-effectiveness of interventions to prevent readmissions.

1. Reuben, D.B., et al., *Development of a Method to Identify Seniors at High Risk for High Hospital Utilization.* Medical Care, 2002. **40**(9): p. 782-793.
2. Hughes, J.S., et al., *Clinical Risk Groups (CRGs): A Classification System for Risk-Adjusted Capitation-Based Payment and Health Care Management.* Medical Care, 2004. **42**(1): p. 81-90.
3. Health, U.D.o. *Improving Chronic Disease Management*. 2004 [cited 2010 28 July 2010]; Available from: http://www.dh.gov.uk/en/Publicationsandstatistics/Publications/PublicationsPolicyAndGuidance/DH_4075214.
4. Pannatoni, L., et al., *Predictive Risk Modelling in Health: Options for New Zealand and Australia.* Australian Health Review, In Press.
5. Roseman, P. *Frequent Adult Medical Admissions Final Report Counties Manukau Acute Demand Management Group* 2003 [cited 2009 10 August, 2009]; Available from: http://www.sah.co.nz/Funded-Services/CCM/docs/reports/FAMAreport.pdf.
6. Billings, J., et al., *Case finding for patients at risk of readmission to hospital: development of algorithm to identify high risk patients.* BMJ, 2006. **333**(7563): p. 327-333.
7. Ham, C., *Chronic Care In The English National Health Service: Progress And Challenges.* Health Aff, 2009. **28**(1): p. 190-201.
8. DeLong, E.R., D.M. DeLong, and D.L. Clarke-Pearson, *Comparing the Areas under Two or More Correlated Receiver Operating Characteristic Curves: A Nonparametric Approach.* Biometrics, 1988. **44**(3): p. 837-845.
9. Fox-Rushby, J. and J. Cairns, *Economic Evaluation*. Understanding Public Health. 2005, London: Open University Press.