Predicting readmissions: poor performance of the LACE index in an older UK population

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Abstract

Introduction: interventions to prevent hospital readmission depend on the identification of patients at risk. The LACE index predicts readmission (and death) and is in clinical use internationally. The LACE index was investigated in an older UK population.

Methods: randomly selected alive-discharge episodes were reviewed. A LACE score was calculated for each patient and assessed using receiver operator characteristic (ROC) curves. A logistic regression model was constructed, compared with the LACE and validated in a separate population.

Results: a total of 507 patients were included with a mean (SD) age of 85 (6.5) years; 17.8% were readmitted and 4.5% died within 30 days. The median LACE score of those readmitted compared with those who were not was 12.5 versus 12 ($P = 0.13$). The Lace index was only a fair predictor of both 30-day readmission and death with $\hat{r}$-statistics of 0.55 and 0.70, respectively. Only the emergency department visit was an independent predictor of readmission, with a $\hat{r}$-statistic of 0.61 for readmission. In a validation cohort of 507 cases, the $\hat{r}$-statistic of the regression model was 0.57.
Conclusion: the LACE index is a poor tool for predicting 30-day readmission in older UK inpatients. The absence of a simple predictive model may limit the benefit of readmission avoidance strategies.

Keywords: readmissions, clinical prediction, elderly, hospital

Introduction

More than one-third of all admissions to hospital in the UK are unplanned, and the yearly cost to the health service is substantial, at about £11 billion [1]. A second admission to hospital in an unplanned manner within a short period following discharge (known as a readmission) is becoming more common, for reasons which are incompletely understood [2]. Readmission rates are particularly high in older people, with 14% of over 75 year olds in the UK being readmitted in the 30 days following discharge. It has been suggested that poor-quality care during the index admission may contribute to readmissions [3]. The perception that such readmissions are a measure of poor-quality care has led to financial penalties for readmissions in the UK and the USA.

Readmissions can be prevented by a number of interventions [4–7]. Such interventions usually include a combination of enhanced discharge planning and post-discharge follow-up. Virtual wards are also being investigated as a method of reducing hospital admissions in patients felt to be at risk of readmission [8]. All these approaches depend on appropriate identification of patients at risk of readmission.

Readmissions can be predicted by complex tools, which are in general not useable in day-to-day clinical practice [9, 10]. Recently, a simpler tool (the LACE Index) has been described in a Canadian population, but was limited to patients without cognitive impairment and excluded nursing home residents [11]. The current study aimed to investigate the use of the LACE index in a population of older UK inpatients. In addition, attempts to improve the LACE index with weighting appropriate for older UK inpatients were undertaken.

Methods

Population

All alive-discharge episodes from the Department of Medicine for the Elderly, Cambridge University Hospitals NHS Foundation Trust for the year ending 31 December 2010 were eligible for inclusion. To minimise the possibility of readmissions to other institutions, only discharges to the local Primary Care Trust were included. Of these, a random sample of cases was selected.

Measurement

Using hospital electronic data, patient demographic and medical details were obtained. The length of stay (LoS) of the index episode and the nature of the admission (planned or emergent) were noted. The number of previous emergency department (ED) attendances within 1 year was obtained. The Charlson comorbidity index (CCI) (using the Romano modification and the Schneesweiss reweighting [12, 13]) was calculated. The ICD-9 codes corresponding to the co-morbidities in the CCI was used to guide the CCI score (as previously validated [13]).

The LACE index (L, LoS; A, Admission type; C, Comorbidity; E, ED attendances) was calculated from the data collected [11]. This is a scale from 0 to 19 where the likelihood of readmission (or death) increases with increasing score. One-month readmissions and 1-month mortality were obtained from the hospital records.

Statistical analysis

The population was described by age, sex and each of the components of the LACE index. Receiver operator characteristic (ROC) curves were constructed for the LACE Index as a predictor of readmission, death or both and area under the curve described using the $c$-statistic. To examine the individual components of the LACE index, univariate analysis was performed with a $t$-test or Mann–Whitney $U$ test. Multivariate analysis was performed using a logistic regression model, constructed by the backward stepwise method based on the likelihood ratio. The outcomes of readmission, death and death or readmission were investigated separately. The regression model was compared with the LACE index as a predictor of readmission, death or both. A further validation cohort was randomly selected to validate the regression model.

Sample size

According to the recommendations of Vergouwe et al., a minimum of 100 events and 100 non-events are required to obtain adequate power for external validation of a prediction tool [14]. Therefore, based on an anticipated rate of readmission or death within 1 month of discharge of 20%, 500 alive-discharge episodes were randomly selected. Similarly, 500 cases were chosen for validation of the regression model. For the logistic regression model, there were five planned covariates and an event rate of 20%. Based on the guidance of Peduzzi et al., the minimum number of cases to include was 250 [15]. Institutional approval was granted in advance of the study.
Results

Five-hundred and fifteen alive-discharges to the relevant primary care trust were reviewed. Of these, eight were excluded (alternative services), and the details of 507 discharges were included in the analysis. The mean (SD) age was 84.8 (6.5) years. The median (IQR) LoS of the index hospital admission was 8 (16) days. The median (IQR) CCI was 3 (4). The median (IQR) number of ED visits in the 6 months prior to the index admission was 0 (1).

A total of 90 cases (17.8%) were readmitted in the month following discharge. Twenty-three cases (4.5%) died, and the cumulative endpoint of 30-day death or readmission was reached in 21.1% of discharges.

The ROC curve of the LACE index as a predictor of 30-day death or readmission is displayed in Figure 1. The c-statistic is fair at 0.60 (95% CI: 0.54–0.66). The c-statistic for the LACE index as a predictor of death is 0.70 (0.59–0.82) and of readmission is 0.55 (0.49–0.61). Although the confidence intervals for the c-statistics overlap and therefore the difference is not statistically significant, the LACE index tended to be a better test for predicting death as opposed to readmission. The c-statistic of the LACE index as a diagnostic test or readmission or death in this population is lower than in the population of Van Walraven et al. [0.684 (95% CI: 0.679–0.691)]. As the confidence intervals do not overlap, the LACE index is a worse test for predicting future readmission or death in this UK population.

When the components of the LACE index and age were compared as pre-specified between those who were and were not readmitted, there were no statistically significant differences. Those who were readmitted had more previous ED visits ($P = 0.001$) (Table 1). When a similar comparison was made for the endpoint of 30-day mortality, those who died had longer LoS ($P = 0.03$), higher CCI ($P = 0.001$), more ED admissions ($P = 0.006$) and higher LACE scores ($P = 0.001$). For the combined endpoint, CCI ($P = 0.015$) and ED visits ($P < 0.001$) were greater in those who were readmitted or died (Table 1).

In a logistic regression, only previous ED visits predicted future readmission [$\text{Exp(B)} = 1.315; P = 0.001$] in a statistically significant but weak model ($R^2 = 0.02$). An ROC curve of the logistic regression model had a c-statistic of 0.61 (0.54–0.67) (Figure 2). In a similarly constructed regression model with 30-day mortality as the outcome, LoS, CCI and ED visits all independently predicted mortality.

Five-hundred and two discharges of 510 selected were included in the second (validation) cohort. The age (mean: 85.2; SD: 5.57 years) and LoS (median: 8; IQR: 15 days) were similar to the initial cohort. The median (IQR) number of ED visits was 0 (1); 0 (1) days for those not readmitted and 1 (2) days for those readmitted ($P = 0.041$); 14.8% of discharge episodes were subsequently readmitted. The c-statistic of the logistic regression model developed from the initial cohort was 0.57 (0.49–0.64) in the validation cohort. The sensitivity and specificity of ED visits with an optimal cut-off of 1 for 30-day readmission were 54 and 47%, respectively.

Discussion

The LACE index is relatively poor at predicting death or readmission, and particularly poor in predicting readmission alone, in an older UK population. The only component of the LACE index which independently predicts readmissions in this population is recurrent ED attendance. This was validated in a second similar cohort of older acute admissions. However, while ED visits are shown to be statistically associated with readmission, as a test, the sensitivity and specificity would be too poor for it to be useful in clinical practice.

There are important differences between the population examined and the Canadian populations in which the LACE index was derived and validated. The Canadian cohort was younger (mean age 59 years), had shorter hospital stays (mean 5 days) and fewer co-morbidities (mean CCI 0.5). This is important, as the absolute readmission

![Figure 1. ROC curves for the LACE Index as a predictor of readmission (left), death (middle) and readmission or death (right).](http://ageing.oxfordjournals.org/)
predictive tools, which have recently been systematically reviewed [21]. The purpose of such tools is twofold: for comparison, allowing risk-adjusted rates to be compared across hospitals; or for clinical use, allowing individuals at risk to be identified. Such clinical tools have the value of allowing resources to prevent readmission to be targeted at those individuals with the highest risk. To date no clinical tool demonstrates sufficient predictive power to allow this approach to work with maximum effectiveness. Of the tools which have been validated, the discriminative ability is generally only fair ($\chi$-statistic range 0.56–0.77). Doctors’ and other health care-providers’ overall opinion of those likely to be readmitted has also been evaluated, but fared no better [22].

Ongoing work is being performed to improve upon available predictive tools, which has been incentivised by the introduction of financial penalties. The NUHFS (a UK-based centre for health-services research and policy analysis) is currently investigating a new tool (the PARR-30) looking specifically at 30-day hospital readmission, which is due to be published in 2012 [23]. This could then be used in conjunction with an intervention, such as virtual wards [8].

It is noteworthy that few tools include markers of illness severity, social determinants of health or overall function. These parameters are clearly more difficult to estimate, and the data are not easily available for risk prediction generation from large databases. However, these same factors may be important predictors of readmission [24]. While it is currently challenging to include such factors in risk-prediction models, it may be that more discriminative models can only be designed by their inclusion. It is particularly interesting that the best-performing clinical predictor (as summarised in the systematic review [21]) used a patient-completed survey of functional status in addition to the administrative data [25]. This approach may be more labour- and resource-intensive, but it allowed better prediction of future readmission.

For this study, the LACE index was chosen as it is a simple tool, and it is clinically useable. It was recently derived, and validated in a large cohort (over 1 million discharges). The LACE index was a better predictor of death

### Table 1. Characteristics of cases with stratification by 30-day death, mortality or both

<table>
<thead>
<tr>
<th></th>
<th>Not readmitted</th>
<th>Readmitted</th>
<th>Not died</th>
<th>Died</th>
<th>Not readmitted or died</th>
<th>Readmitted or died</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length of stay</td>
<td>9 (16)</td>
<td>8 (12)</td>
<td>8 (16)*</td>
<td>19 (25)*</td>
<td>8 (16)</td>
<td>9 (16)</td>
</tr>
<tr>
<td>Charlson comorbidity index</td>
<td>3 (4)</td>
<td>4 (3)</td>
<td>3 (4)**</td>
<td>5 (4)**</td>
<td>3 (4)*</td>
<td>4 (4)*</td>
</tr>
<tr>
<td>6 month ED attendances</td>
<td>0 (1)***</td>
<td>1 (2)***</td>
<td>0 (1)**</td>
<td>1 (2)**</td>
<td>0 (1)***</td>
<td>1 (2)***</td>
</tr>
<tr>
<td>Age</td>
<td>84.6 (6.5)</td>
<td>85.4 (6.6)</td>
<td>84.7 (6.5)</td>
<td>85.7 (6.4)</td>
<td>84.6 (6.5)</td>
<td>85.5 (6.6)</td>
</tr>
<tr>
<td>LACE</td>
<td>12 (5)</td>
<td>12.5 (4)</td>
<td>12 (5)**</td>
<td>14 (5)**</td>
<td>12 (5)**</td>
<td>13 (5)**</td>
</tr>
</tbody>
</table>

Statistically significant differences highlighted. Values are mean (SD) for age and median (IQR) for other variables.

* $P \leq 0.05$.

** $P \leq 0.01$.

*** $P \leq 0.001$.

Figure 2. ROC curve of LACE score (dark grey) and derived logistic regression model (light grey) as a determinant of readmission.

rate is higher in the over 70s (though not a continuous increase as seen in this study), making this a target group for service developments aimed at preventing unnecessary readmissions. This study reinforces the point that predictive models developed in one population may not be applicable to other populations [16].

There are clearly very many factors underlying readmission to hospital. Some of these will be non-modifiable, such as the occurrence of disease. However, the health care factors which predispose to readmission, such as suboptimal care, may be modifiable. With pressure from LoS targets and increasing hospital resource use, it is possible that older people with complex needs are being discharged earlier than would be ideal [17]. This hypothesis has led to health services considering higher readmission rates to be a marker of poor quality care.

The NHS has plans to reduce readmissions by imposing financial penalties for unplanned readmissions [18] and in the USA, readmissions are considered a measure of quality of care, with reimbursements adjusted accordingly [19]. However, it is perhaps simplistic to conclude that a readmission reflects poor care. For example, it has been seen that hospitals with lower inpatient mortality have higher 30-day readmissions [20]. It is likely that a consequence of good-quality care will be that more people will survive to discharge, some of whom may be in need of medical care again in the subsequent month. This serves to illustrate the unsuitability of readmission rate alone as a marker of quality of care. While it is easy to measure, interpretation is more complex.

It is noteworthy that few tools include markers of illness severity, social determinants of health or overall function. These parameters are clearly more difficult to estimate, and the data are not easily available for risk prediction generation from large databases. However, these same factors may be important predictors of readmission [24]. While it is currently challenging to include such factors in risk-prediction models, it may be that more discriminative models can only be designed by their inclusion. It is particularly interesting that the best-performing clinical predictor (as summarised in the systematic review [21]) used a patient-completed survey of functional status in addition to the administrative data [25]. This approach may be more labour- and resource-intensive, but it allowed better prediction of future readmission.

For this study, the LACE index was chosen as it is a simple tool, and it is clinically useable. It was recently derived, and validated in a large cohort (over 1 million discharges). The LACE index was a better predictor of death.
than of readmission, mirroring the findings of Van Walraven et al. This is perhaps not surprising, as a major facet of the LACE index is the CCI, which is weighted by the mortality associated with different co-morbidities. Age is also a risk factor for death.

Attempts to re-weight the components of the LACE index for an older UK population could not be undertaken, as the individual components were not independently associated with readmission. Only ED visits were included in the regression model. Such a model is unlikely to be clinically useful, due the phenomenon of 'regression to the mean', where patients have an intense period of recurrent admission, following which the readmission rate returns to that of the general population [26]. This approach would essentially identify patients at a point when it may be too late to prevent their hospital admissions.

This study had sufficient cases to appropriately validate both the LACE index, and the logistic regression derived, had complete data on all discharges, and evaluated a recent UK inpatient cohort. The results will be applicable to similar UK populations. A retrospective cohort was used, with the associated limitations. However, given the nature of the data which were reliably available, this should not be a major weakness. Just one predictive model was assessed in this population, and was chosen for its suitability and strengths as described. It is also possible that some cases in our study were readmitted to other hospitals, but this effect was minimised by including discharges from the local PCT only.

In developing readmission prediction tools, it is preferable that individual patient factors are included. This may serve to improve their ability to successfully predict readmissions. In addition, models developed in other populations should always be validated in the target population before being utilised, as in this case with the LACE index. The authors of a recent study on readmission prediction tools found them to lack the necessary sophistication to capture the complexity of (unplanned) readmissions [27]. Until such time as there is improved prediction, the benefit from readmission reduction interventions may not be fully realised.

Key points

- Hospital readmissions are frequent, costly and potentially preventable.
- Prevention of readmission requires case finding, which depends on prediction tools.
- The LACE index is a popular, simple prediction tool. It fared poorly in a UK population.
- More detailed patient-level information is required to improve the performance of readmission prediction tools.

Acknowledgements

We wish to acknowledge Elizabeth Merrall, Medical Statistician and the Centre for Applied Medical Statistics, Institute of Public Health, Cambridge for the assistance at the design stage of this project.

Conflicts of interest

None declared.

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Will-to-live and survival in a 10-year follow-up among older people

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Abstract

Background: there is little research how older people’s will-to-live predicts their survival.

Objective: to investigate how many years home-dwelling older people wish to live and how this will-to-live predicts their survival.

Methods: as a part of the Drugs and Evidence-Based Medicine in the Elderly (DEBATE) study, 400 home-dwelling individuals aged 75–90 were recruited into a cardiovascular prevention trial in Helsinki. In 2000, a questionnaire about the wishes of their remaining life was completed by 283 participants. Participants were inquired how many years they would still wish to live, and divided into three groups according to their response: group 1: wishes to live <5 years, group 2: 5–10 years, group 3: >10 years. Mortality was confirmed from central registers during a 10-year follow-up. The adjusted Cox proportional hazard model was used to determine how will-to-live predicted survival.

Results: in group 1 wishing to live less than 5 years, the mean age and the Charlson comorbidity index were the highest, and subjective health the poorest. There were no differences between the groups in cognitive functioning or feeling