A prospective cohort study of two predictor models for 30-day emergency readmission in older patients

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Abstract
Aim: To undertake a prospective study of the accuracy of two models (LACE and BOOST) in predicting unplanned hospital readmission in older patients (>75 years).
Methods: Data were collected from a single centre prospectively on 110 patients over 75 years old admitted to the acute medical unit. Follow-up was conducted at 30 days. The primary outcome was the c-statistic for both models.
Results: The readmission rate was 32.7% and median age 82 years, and both BOOST and LACE scores were significantly higher in those readmitted compared with those who were not. C-statistics were calculated for both tools with BOOST score 0.667 (95% CI 0.559-0.775, \( P = .005 \)) and LACE index 0.685 (95% CI 0.579-0.792, \( P = .002 \)).
Conclusion: In this prospective study, both the BOOST and LACE scores were found to be significant yet poor, predictive models of hospital readmission. Recent hospitalisation (within the previous 6 months) was found to be the most significant contributing factor.

1 | INTRODUCTION

Preventing hospital readmission is a common and costly issue, and emergency readmission within 30 days of discharge is used as a measure of care and often deemed avoidable, although nonelective readmissions are often not preventable or predictable. Recent analysis by the Nuffield Trust reported an increase of 19.2% in 30-day readmissions in England between 2010/2011 and 2016/2017 from 1 157 570 to 1 379 790.1

Several authors have developed predictive tools to assist clinicians to identify patients at risk of death or readmission within 30 days of discharge.2-6 Reasons for hospital readmission often relate to the person’s age, underlying comorbidities (especially conditions such as heart failure and respiratory conditions such as chronic obstructive pulmonary disease, COPD) and number of medications.7,8 Several authors have highlighted the patient-led factors in predicting readmissions with age being a significant predictor.3,6 Some studies reported the importance of underlying comorbidities as being strong predictors of readmission,4 and a recent comparative study identified high comorbidity scores using the Charlson Comorbidity Index, excessive polypharmacy and living in the community with home care being at greater risk of readmission.9 However, several systematic reviews have highlighted that the majority of the predictive tools had poor discriminatory ability.10-12 The LACE index identified four variables that were predictive (length of stay, acuity, comorbidities and emergency department use) and was found to have reasonable discrimination13; the BOOST tool identified eight variables.14 Cotter et al (2012) reported that one variable, a visit to the emergency department, as an independent predictor of readmission in older patients with a c-statistic of 0.61 for readmission. A recent examination of BOOST in the United States demonstrated a similar c-statistic of 0.631 and was the first study to validate the BOOST 8 P tool in older...
patients using logistic regression modelling and using nursing documentation. However, little data are available on their use and application within the UK population.

The aim of the study was to undertake a prospective study to determine the accuracy of two models (LACE and BOOST) in predicting unplanned hospital readmission in older patients in the United Kingdom.

2 | METHODS

2.1 | Study design

We conducted a single centre, prospective cohort study to determine the accuracy of two models at predicting unplanned readmissions in those aged 75 and older who were initially admitted with an acute medical condition. Data collection took place from February to April 2019 at a large teaching hospital in central London. Data were collected by authors (MA, BA, MB and MW) prospectively from patient interviews, electronic health records and through discussion with the health care team. All data collectors were trained on the use of a standardised proforma for data collection. All proforma were kept secured on-site in conformance with trust information governance policy. This proforma included patient demographics, BOOST score and LACE index with individual subsections. The proforma was adapted and agreed by the authors (MA, VS and GL) prior to starting the study. Patient demographics consisted of age, gender and presenting complaint. The BOOST scoring system consisted of eight parts (Table 1). On day 30, patients were screened for readmission using the trust’s electronic health record.

As the BOOST 8Ps scoring system does not specifically define the criteria required to score in each category, to prevent bias, we implemented an objective threshold for each category using a methodology previously used. In the case of “poor health literacy,” we defined this as an inability to answer two thirds of the teach back assessment questions. For “frailty” (occasionally referred to as physical limitations in the tool) we opted to use the Clinical Frailty Scale16 with a score of ≥5 giving a point in the BOOST tool. Depression was scored if there was any recorded diagnosis of depression or positive depression screening tool such as the Patient Health Questionnaire (PHQ)-9. For the purposes of further analysis, we collected information on which criteria each patient met to earn a point in each category. For example, data collectors were asked to circle each medication a patient was taking when scoring the problem medication section. The total BOOST score was summed in the end out of a total of 8 points. The total LACE index score was calculated out of 19.

Neither patients nor the public was involved in the conception, design or implementation of this study. Ethics approval was not required as it was deemed a service evaluation.

2.2 | Inclusion and exclusion criteria

Inclusion

- Aged 75 years or older.
- Admitted to acute admissions ward from Monday to Friday.

Exclusion

- Patients not discharged but transferred from the acute admissions ward to inpatient wards.
- Patients who died prior to the 30-day follow-up period.

2.3 | Outcome measures

The primary outcome measure was readmission at 30 days as recorded by electronic patient records. Secondary outcomes included the individual predictor model components and the sensitivity, specificity and odds of high- and low-risk LACE and BOOST patient groups.

2.4 | Statistical analysis

The area under the receiver operating characteristic (AUROC) curve (also termed the c-statistic and this is the term we will be using in this paper) was used as the primary measure of accuracy for the BOOST and LACE scoring systems. A power calculation was completed using the R-based web tool easyROC with sample size determined using a type I error of 0.05, a power of 0.8, a c-statistic of 0.7 and an allocation ratio of 6. The suggested sample size was 98 with 14 positive and 84 negative cases. The allocation ratio was
The BOOST index consisted of eight categories:
1. Problem medication
   a. Prescribed >9 medications, or
   b. One of: insulin, anticoagulants, oral hypoglycaemics, dual antithrombotic therapy, digoxin, or narcotics
2. Psychological
   a. Previous PHQ-9 performed, or depression history
3. Principal diagnosis
   a. One of: cancer, stroke, DM, COPD, or heart failure
4. Frailty
   a. Clinical frailty scale score ≥5 (Score: ___)
5. Poor health literature
   a. Inability to perform ‘teach back’ for 2/3 of,
      (i) "What is your main problem?"
      (ii) "What do you need to do after leaving hospital?"
      (iii) "Why is it important that you do this?"
6. Poor patient support
   a. "Do you have someone to help at home should you need it?"
7. Prior hospitalisation
   a. Unplanned admission in past 6 months
8. Palliation
   a. Would I be surprised if this patient died in the next year, or
   b. Does this patient have an advanced or progressive serious illness?

The LACE index consisted of four categories:
1. Length of stay: 1 day (+1), 2 days (+2), 3 days (+3), 4-6 days (+4), 7-13 days (+5), ≥14 days (+7)
2. Admission type: nonemergency (+0), emergency (+3)
3. Comorbidities: Charlson Index score 1 (+1), 2 (+2), 3 (+3), ≥4 (+5)
4. Emergency attendances in past 6 months: 0 (+0), 1 (+1), 2 (+2), 3 (+3), ≥4 (+4)

Abbreviations: COPD, chronic obstructive pulmonary disease; DM, diabetes mellitus; PHQ-9, Patient Health Questionnaire.

predicted from literature suggesting a readmission rate of 14% in the older patients.19

All statistical analyses, apart from the ROC power calculation, were performed using SPSS Statistics version 25.20 Continuous variables were compared for statistical significance to an alpha of <.05 using Mann Whitney U tests. Categorical data were compared for statistical significance to an alpha of <.05 using chi-square tests. Prior to binary logistic regression, analysis variables were screened for collinearity with all values showing an acceptable level of tolerance (VIF <10). Univariate and simultaneous multivariate binary logistic regessions were carried out using the enter method to compare the components of the BOOST and LACE models. Model 1 considered each of the eight BOOST factors along with their sub-components where variables were not dichotomous. Model 2 was composed of the eight BOOST score components alone. Model 3 was of the LACE index components. In this model emergency admissions were excluded as 100% of cases were classified as an emergency for both readmission and no readmission.

Youden’s index was calculated for each point in the BOOST score and LACE index, with the maximum value representing the ideal cut-off point for screening. Chi-squared testing to alpha <.05 was used to determine significance in chance of readmission for high- and low-risk BOOST and LACE patients.

3 | RESULTS

3.1 | Patient characteristics

We recorded 184 admissions (from 178 patients) of which 110 met our inclusion criteria and were included for 30-day follow-up. Of those not included 69 were transferred from the acute admissions ward to an inpatient ward, and 5 died prior to follow-up. Of those included for follow-up, one patient accounted for 3 (8.3%) readmissions during the 30-day study period. The readmission rate for those included was 32.7%. The median age was 82 years (IQR 73-91), and 61.8% of patients were female (Table 2).

3.2 | BOOST score

Median BOOST score for all patients was 4.0 (IQR ±1.0). The median BOOST score for those readmitted (4.0, IQR ±2.0) was found to be significantly greater than for those not readmitted (3.0, IQR ±2.0, P = .006). The frequency of contributing factors for the BOOST score is given in Table 2 as number of patients (% of readmission status). The most commonly scored BOOST component was for a high-risk principal diagnosis (76.4%), and the least scored was for depression history (10.0%).

3.3 | LACE index

Median LACE index for all patients was 12.0 (IQR ±2.0). Median LACE index was significantly greater for those readmitted (11.5, IQR ±2.0) compared with those not readmitted (10.0, IQR ±1.0, P = .001). By the nature of the acute admissions ward, 100% of patients were classified as an emergency admission and scored 3 points in this section.

3.4 | Univariate binary logistic regression

The univariate binary logistic regression analysis is presented in Table 3. Increasing BOOST score was a significant contributor to patient readmission with an odds ratio of 1.5 (95% CI 1.1-2.0). Components of the BOOST score which significantly contributed to risk of readmission include diabetes mellitus diagnosis (OR 2.8, 95% CI 1.2-6.4), >9 prescribed medications (OR 2.4, 95% CI 1.0-5.6), prescribed insulin (OR 4.7, 95% CI 1.1-20.0) and recent hospitalisation (OR 4.8, 95% CI 2.0-11.5).

Increasing LACE index was also significantly associated with readmission with an odds ratio of 1.5 (95% CI 1.2-2.1). The only statistically significant component of the LACE index was number of hospitalisations in the prior 6 months which had an odds ratio of 2.0 (95% CI 1.3-3.1). Odds for emergency admission and comorbidity index were skewed as all indexed patients were classified as an emergency attendance, and all but one patient obtained a comorbidity index score of 5.
### 3.5 Multivariate binary logistic regression

The multivariate binary logistic regression analysis is presented in Table 4. When considering the BOOST score with subcomponents (Model 1), the only value which significantly contributed to readmission was recent hospitalisation which had an odds ratio of 4.6 (95% CI 1.6-13.6). When modelling the BOOST score without the subcomponents (Model 2), the only significant component was recent hospitalisation which had an odds ratio of 4.4 (95% CI 1.7-11.3). In the LACE index (Model 3), recent attendance was also the only significant contributor with an odds ratio of 2.0 (95% CI 1.3-3.0). All three models were able to predict roughly three quarters of cases, and in each the only significant predictor of readmissions was related to the number of recent hospitalisations.
TABLE 4  Multivariate binary logistic regression analysis of the BOOST and LACE scores.

| Variable                        | Odds ratio | 95% CI     | P value |
|---------------------------------|------------|------------|---------|
| Model 1: BOOST score components and subcomponents |            |            |         |
| Risk diagnosis                  | 3.14       | 0.45       | 21.94   | .248    |
| Diabetes mellitus               | 1.51       | 0.31       | 7.50    | .611    |
| Cancer                          | 0.44       | 0.10       | 1.97    | .282    |
| COPD                            | 1.04       | 0.25       | 4.38    | .958    |
| Heart failure                   | 0.60       | 0.08       | 4.55    | .623    |
| Stroke                          | 0.57       | 0.08       | 4.03    | .572    |
| Problem meds                    | 0.33       | 0.05       | 2.10    | .240    |
| >9 medications                  | 2.63       | 0.59       | 11.75   | .206    |
| Oral hypoglycaemics             | 1.73       | 0.28       | 10.50   | .553    |
| Anticoagulants                  | 0.83       | 0.15       | 4.51    | .833    |
| Narcotics                       | 1.20       | 0.24       | 5.96    | .825    |
| Insulin                         | 3.77       | 0.37       | 38.24   | .261    |
| Digoxin                         | 0.27       | 0.02       | 4.32    | .353    |
| Dual antiplatelet therapy       | 1.32       | 0.05       | 37.18   | .870    |
| Frailty                         | 1.67       | 0.56       | 4.99    | .356    |
| Palliative                      | 0.71       | 0.22       | 2.35    | .580    |
| Recent hospitalisation          | 4.62       | 1.57       | 13.62   | .005*   |
| Poor health literacy            | 1.25       | 0.03       | 4.32    | .719    |
| Poor support                    | 1.30       | 0.33       | 5.12    | .705    |
| Depression history              | 1.14       | 0.26       | 4.93    | .861    |

Model 1 summary: overall percentage = 71.8%, Nagelkerke R² = .308

Model 2: BOOST score components

| Variable                        | Odds ratio | 95% CI     | P value |
|---------------------------------|------------|------------|---------|
| Problem meds                    | 0.93       | 0.35       | 2.52    | .893    |
| Depression history              | 1.18       | 0.29       | 4.80    | .814    |
| Risk diagnosis                  | 2.33       | 0.68       | 8.00    | .179    |
| Frailty                         | 1.66       | 0.65       | 4.27    | .292    |
| Poor health literacy            | 1.00       | 0.36       | 2.76    | .993    |
| Poor support                    | 1.12       | 0.35       | 3.62    | .848    |
| Recent hospitalisation          | 4.39       | 1.71       | 11.32   | .002*   |
| Palliative                      | 0.77       | 0.29       | 2.05    | .597    |

Model 2 summary: Overall percentage = 74.5%, Nagelkerke R² = .197

Model 3: LACE index components

| Variable                        | Odds ratio | 95% CI     | P value |
|---------------------------------|------------|------------|---------|
| Length of stay score            | 1.17       | 0.78       | 2.25    | .443    |
| Emergency admission             | —          | —          | —       | —       |
| Comorbidity index score         | —          | 0.00       | —       | .999    |
| Recent attendance score         | 1.99       | 1.31       | 3.03    | .001*   |

Model 3 summary: Overall percentage = 72.7%, Nagelkerke R² = .165

Note: The BOOST score was split across two models to consider the contribution of both components and subcomponents. *P < .05.

3.6 | Receiver operating characteristic (ROC) analysis

The resulting c-statistics were 0.667 (95% CI 0.559-0.775) for the BOOST score and 0.685 (95% CI 0.579-0.792) for the LACE index (Figure 1).

Cut-off scores for optimal sensitivity and specificity in each model were found to be a BOOST score of 4 (YI = 0.28) and a LACE index of 11 (YI = 0.29). Patients with a BOOST score of 4 or more would be classified as “high-risk” and have a sensitivity of 69.4% and specificity of 58.1% for predicting readmission. This provides a positive likelihood ratio of readmission of 1.66 for high-risk BOOST patients. The high-risk category for the LACE index was determined to be 11 or more, with a sensitivity of 77.8% and a specificity of 51.4% for readmission. This provides a positive likelihood ratio of readmission of 1.60 for high-risk LACE patients.

A readmission rate of 20.4% (n = 11) was seen in those with a low-risk BOOST score and a 44.6% (n = 25) readmission rate in the high-risk category. Those who had a high-risk BOOST score were significantly more likely to be re-admitted (P = .007) with odds of readmission 3.2 (95% CI 1.4-7.4) times higher than low-risk patients. Those in the low-risk LACE category had a readmission rate of 17.4% (n = 8) and in the high-risk category 43.8% (n = 28). Those with a high-risk LACE index were also significantly more likely to be re-admitted (P = .004) with odds of reattendance 3.7 (95% CI 1.5-9.2) times higher than low-risk patients.

4 | DISCUSSION

This is the first study to our knowledge that evaluates the LACE and BOOST predictor models in a prospective study of older patients >75 years. Mean BOOST score was 4.0 (IQR ±1.0) and was similar to an earlier retrospective study in another London hospital of 324 patients. The LACE mean score of 12 (±2.0) is similar to other studies with slightly higher scores in those readmitted compared with those who were not readmitted.

The readmission rate was 33% in this study, and older patients had higher readmission rates; this differs from others where rates of 8% to 22% have been reported. However, neither of these studies explicitly examined older patients, and thus, our readmission rate is not unexpected. The higher readmission rate may have impacted our data in lowering the number of predicted nonevents in our power calculation, which used the literature readmission rate of 14% for our population. This may have led our study to be underpowered.

The c-statistic was 0.667 for BOOST and 0.685 for LACE, both of which are significant predictors of readmission, and the results are comparable to previous studies. However, neither of these studies explicitly examined older patients, and thus, our readmission rate is not unexpected. The higher readmission rate may have impacted our data in lowering the number of predicted nonevents in our power calculation, which used the literature readmission rate of 14% for our population. This may have led our study to be underpowered.

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Interestingly, the systematic review, which included BOOST but not LACE, commented that few of the tools included overall health, illness severity and social determinants of health. Sieck et al were the first to include social determinants of health whilst examining readmission prediction and undoubtedly, this is an important aspect that should be considered when exploring readmission predictors.

Relating to the multivariate analysis, the strongest predictor of readmission is previous admission in this cohort, and hospital readmission continues to be a common phenomenon and perhaps not unexpected. Given this, we perhaps need to examine the issue in a different manner and focus on transitional care following discharge from hospital for this cohort of patients as a way to prevent/reduce hospital readmission. There are now established hospital in the home and transitional programmes that allow early hospital discharge and prevent hospital admission are beneficial. A systematic review of interventions to reduce early hospital readmissions concluded that interventions were complex with more recent ones less effective in their review from 2009 to 2013. Singaporean-based RCT showed some positive results but again highlighted the issues facing clinicians with patients with multiple comorbidity and complex care needs. Coordination of care has been cited as an issue, and this continues to be a problem in the United Kingdom. The recurrent theme of previous hospitalisations is a strong indicator of future readmission; it may be that predictor models do not have benefit over a well-performed history with emphasis on previous admissions. This would be an area worth future investigation.

It may be that patients require a "step-down" or managed approach following hospital discharge, and the role of a hospital in the home has the potential to improve postdischarge outcomes, and a Cochrane review from 2016 acknowledged that although hospital in the home may be an effective alternative, there was not enough robust research to demonstrate this. Within the local area, the home service set up in 2014 manages 300-400 patients per month for short-term acute follow-up with positive results in terms of patient satisfaction but did not demonstrate significant reduction in local emergency department attendances. Given that hospital in the home services are now embedded into the healthcare system and integrated care is being established around the country, an exploration of targeted services for patients with high BOOST and/or LACE scores is required. This would determine if early identification of patients who had high scores and were referred for hospital in the home services translates to a lower readmission rate and better clinical outcomes for patients. Clearly, further research is needed on various hospitals in the home programmes as they are not standardised service.

A limitation of this study lies in the selection of a subgroup of patients that were admitted and discharged in a short time, mostly with length of stays less than 2 weeks and not transferred to an inpatient ward. This study evaluates the use of the BOOST and LACE tools for recognising risk factors for readmission in these patients but does not directly evaluate its use in those patients who are transferred from the acute medical ward to inpatient wards for greater lengths...
of stay. However, we feel that the use of the predictor models in this study would represent the way these models would be used in the context of an acute medical department. It is also possible that patients may have been readmitted to a hospital outside of our trust and as such would not be picked up at 30-day screening, which would underestimate the recorded readmission rate. We did not include deceased patients in this study as only the LACE index was originally designed with this as an intended outcome.13 We acknowledge that this may not represent the global population, and future studies should evaluate this as an outcome in the BOOST tool. We also believe that this study would have benefited from recording the reason for readmission to form a more complete picture; however, this is an area which may be explored in the future.

This single centre, prospective cohort study aimed to determine the accuracy of two models at predicting unplanned readmissions in those aged 75 and older. We have demonstrated that whilst the mean BOOST and LACE scores for those readmitted was significantly higher than those not readmitted, the accuracy for both models overall is poor. Whilst the models accurately predicted roughly 70% of readmissions, sensitivity and specificity could stand to be improved. Our results show that the strongest predictor of readmission is previous admissions, which highlights the importance of preventing hospital admissions in the first place. It may be that we need to focus on education intervention to increase patient involvement in their care and ongoing management of their health. This approach has the ability to improve continuity of care and along with care coordination; there could be some benefit for decreased hospitalisations. The BOOST tool has the potential to provide a pathway for quality improvement where interventions (such as teach back) based on identified risk factors (ie literacy) could help in preventing readmissions, but this has not been evaluated here.

Predicting hospital readmission remains a complex task, and any tool needs to be clinically relevant and reliably measured. Further prospective studies using these predictive tools may be useful in planning transitioned and hospital in the home programmes for those at high-risk of readmission.

DISCLOSURES
The authors declare that they have no conflicts of interest.

DATA AVAILABILITY STATEMENT
The data that support the findings of this study are available from the corresponding author upon reasonable request.

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