A prospective cohort study comparing two predictor models for 30-day emergency readmission in the elderly.

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Abstract

Aim: To undertake a prospective study of the efficacy of two models (LACE and BOOST) in predicting unplanned hospital readmission. Methods: Data were collected from a single centre prospectively over a continuous 30-day period on all patients over 75 years old admitted to the acute medical unit. The primary outcome was the area under the curve for both models. Results: Area under the curve were calculated for both tools with BOOST score 0.667 (95% CI: 0.559-0.775, p=0.005) and C-statistic for LACE index 0.685 (95% CI: 0.579-0.792, p=0.002). Conclusion: In this prospective study, both the BOOST and LACE scores were found to be significant predictive models of hospital readmission. Recent hospitalisation was found to be the most significant contributing factor. Key Words: Elderly, prediction, readmission

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Conclusion : In this prospective study, both the BOOST and LACE scores were found to be significant predictive models of hospital readmission. Recent hospitalisation was found to be the most significant contributing factor.

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Key Points

- Readmission rate was 32.7% with median age 82 years (IQR 73-91) and 61.8% female
- The mean BOOST and LACE scores for those readmitted was significantly higher than those not readmitted.

- Area under the curve analysis signifies both the BOOST and LACE scores have good predictive capacity for readmission.
- The most significant contributing factor from both scores was another hospital admission in the preceding 6 months.

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 non-elective 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 2010/11 and 2016/17 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 [2,3,4,5,6]. However, several systematic reviews have highlighted the majority of the predictive tools had poor discriminatory ability [7,8,9]. The LACE index identified four variables that were predictive (length of stay, acuity, comorbidities and emergency department use) and was found to have reasonable discrimination [10], the BOOST tool identified eight variables [11]. However little data is available on their use and application within the UK population.

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

Methods

Study design

We conducted a single centre, prospective cohort study to determine the efficacy 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. All patients 75 years of age and older admitted to the acute admissions ward during a continuous 30-day period were included in the study. Exclusion criteria included patients transferred from the acute admissions ward to another inpatient ward and those who died prior to 30-days post-discharge. Data collection was carried out Monday to Friday and as such patients both admitted and discharged within the same Saturday-Sunday period may have been omitted from collection. The primary outcome measure was the area under the receiver operating characteristic curve (AUROC), also termed the c-statistic, for the BOOST and LACE scoring systems. A power calculation was completed using the R-based web tool easyROC [12] 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 152 with 19 positive and 133 negative cases. The allocation ratio was predicted from literature suggesting a readmission rate of 14% in the elderly [13]. Secondary outcomes included the significance of individual predictor model components, and the sensitivity, specificity, and odds of high and low risk LACE and BOOST patient groups.

Patient and public involvement

Neither patients or the public were involved in the conception, design, or implementation of this study.

Data collection

Data was 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. This proforma included patient demographics, BOOST score, and LACE index with individual subsections. The proforma was adapted and agreed by the authors (MA, VS, GL) prior to starting the study. Patient demographics consisted of age, gender, and presenting complaint. The BOOST scoring system consisted of 8 parts (**Table 1**).

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 [11]. In the case of 'poor health literacy', we defined this as an inability to answer 2/3 of the teach back assessment questions. 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.

All proforma were kept secured on-site in conformance with trust information governance policy.

Statistical analysis

All statistical analyses, apart from the ROC power calculation, were performed using SPSS Statistics version 25 [14]. Continuous variables were compared for statistical significance to an alpha of <0.05 using Mann Whitney U tests. Categorical data were compared for statistical significance to an alpha of <0.05 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 regressions were carried out to compare the components of the BOOST and LACE models. Model accuracy was determined by calculating the area under the receiver operating characteristic curve. 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 <0.05 was used to determine significance in chance of readmission for high and low risk BOOST and LACE patients.

Results

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 onwards to an inpatient ward, and 5 died prior to discharge. 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. There was no significant difference in age or sex ($p = 0.813$ and $p = 0.601$ respectively) between those readmitted and not readmitted (**Table 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 higher than for those not readmitted (3.0, IQR ± 2.0) (Mann Whitney U, $p = 0.004$). The frequency of contributing factors for the BOOST score are 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%). Cross tabulation with Pearson chi-square testing found a significantly higher number of patients readmitted with diabetes mellitus, taking >9 regular medications, prescribed insulin, or with an unplanned admission in the past 6 months ($p = 0.013$, 0.043, 0.024, and <0.001 respectively) compared to those not readmitted.

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 to those not readmitted (10.0, IQR ± 1.0) (Mann Whitney U, $p = 0.001$). Frequency of LACE index variables are provided in Table 1 as median score (IQR). By the nature of the acute admissions ward, 100% of patients were classified as an emergency admission and scored 3 points in this section. Number of emergency attendances in the past 6- month was significantly higher in those readmitted compared to those not readmitted (Mann Whitney U, $p < 0.001$).

Univariate binary logistic regression

Univariate binary logistic regression was performed using the enter method to determine contribution of independent variables towards patient readmission (**Table 3**). Neither age nor sex were significant contributing factors to patient reattendance. Increasing BOOST score was a significant contributor to patient readmission

with an odds ratio of 1.5 (95% CI 1.1 – 2.0, p = 0.006). Components of the BOOST score which significantly contributed to risk of readmission include diabetes mellitus diagnosis (OR 2.8, p = 0.014), >9 prescribed medications (OR 2.4, p = 0.045), prescribed insulin (OR 4.7, p = 0.036), and recent hospitalisation (OR 4.8, p = <0.001). Increasing LACE index was also significantly associated with readmission with an odds ratio of 1.5 (95% CI 1.2 – 2.1, p = 0.003). 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, p = 0.001). 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.

Multivariate binary logistic regression

A multivariate binary logistic regression analysis was undertaken to determine the significance of contributors to the BOOST score and LACE index (**Table 4**). Model 1 considered each of the eight BOOST factors along with their sub-components where variables were not dichotomous. This model correctly predicted 71.8% of cases with a pseudo-R^2 value of 0.308. The only value in this model which significantly contributed to readmission was recent hospitalisation (p = 0.005) which had an odds ratio of 4.6 (95% CI 1.6 – 13.6). Model 2 was composed of the eight BOOST score components alone. This model accurately predicted the highest number of cases with 74.5% of correct cases identified, and a pseudo-R^2value of 0.197. Again, the only significant component was recent hospitalisation (p = 0.002) which had an odds ratio of 4.4 (95% CI 1.7 – 11.3). Model 3 was of the LACE index components. In this model emergency admissions were excluded as 100% of cases were classified as an emergency fo both readmisison and no readmisison. This model accurately predicted 72.7% of cases with a pseudo-R^2value of 0.165. Recent attendance was the only significant contributor (p = 0.001) with an odds ratio of 2.0 (95% CI 1.3 – 3.0). Taken together 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. The BOOST score found a higher odds ratio associated with recent attendance compared to the LACE index which is likely due to the different nature of scoring this section; the BOOST score is binary for any attendance within past six months, and the LACE index provides a higher score for more attendances

Area under the receiver operating characteristic (ROC) curve

An area under the receiver operating characteristic curve analysis was performed for both the BOOST score and LACE index. The resulting c-statistics were 0.667 (955 CI 0.559 – 0.775, p = 0.005) for the BOOST score, and 0.685 (95% CI 0.579 – 0.792, p = 0.002) for the LACE index, demonstrating both as significant predictors of readmission (**Figure 1**). We believe the similarity in these c-statistics to demonstrate equivalent accuracy in predicting readmissions by either model.

Cut-off scores for optimal sensitivity and specificity in each model as determined by the maximum Youden's index (YI) 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. 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.

Cross tabulation demonstrated a readmission rate of 20.4% in those with a low-risk BOOST score, and a 44.6% readmission rate in the high-risk category. Pearson chi-squared testing showed those who had a high-risk BOOST score were significantly more likely to be readmitted (χ^2 = 7.356, N = 110, P = 0.007). Those in the low-risk LACE category had a readmission rate of 17.4%, and in the high-risk category 43.8%, thus making it a poor rule-out test, similar to BOOST at 20.4%. Those with a high-risk LACE index were significantly more likely to be readmitted (χ^2 = 8.446, N = 110, P = 0.004). High-risk BOOST patients had odds of reattendance 2.5 times higher than low-risk patients, and high-risk LACE patients had odds of reattendance 3.0 times higher than low-risk patients.

Discussion

This is the first study that compares two predictive scores in a prospective study. Mean BOOST score was

4.0 (IQR ± 1.0) and was similar to an earlier retrospective study in another London hospital of 324 patients [11]. The LACE mean score of 12 (± 2.0) is similar to other studies with slightly higher scores in those re-admitted compared to those who were not re-admitted [15].

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 [10,15]. 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 non-events in our power calculation (which used the literature readmission rate of 14% for our population. This may have led our study to be underpowered.

Examining the area under the receiver operating characteristic (ROC) curve 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 [9,10,15]. AUCs of less than 0.7 are deemed 'good' predictive capacity which reflects the overlap in predictions of those readmitted versus those who are not. The discriminatory ability of LACE has previously been reported as poor in the elderly population [16] and systematic review found that most models performed poorly (mainly in US population), but suggested that they may be useful with wider implementation needed [7]. This was similar to our findings with both BOOST and LACE having poor (but significant) discrimination for this group. 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 [7].

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 [9]. 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 [17,18,19,20]. 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 [8]. Singaporean-based RCT showed some positive results but again highlighted the issues facing clinicians with patients with multiple comorbidity and complex care needs [21]. Co-ordination of care has been cited as an issue and this continues to be a problem in the UK [22]. The recurrent theme of previous hospitalisations as 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 post-discharge outcomes [19,23]. 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 [24], but did not demonstrate significant reduction in local emergency department attendances [25]. 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 the various hospital in the home programmes as they are not standardised service.

A limitation of this study lies in the selection of a sub-group of patients that were admitted and discharged in a short time, mostly with length of stays less than two weeks, and not transferred to an inpatient ward. This study validates the use of the BOOST tool for recognising risk factors for readmission in these patients, but does not directly validate its use in those patients who are admitted to inpatient wards for greater lengths of stay. However, unlike the LACE score the BOOST tool does not select for length of stay and is designed only to flag patients with risk factors for readmission regardless of duration.

This single centre, prospective cohort study aimed to determine the efficacy of two models at predicting

unplanned readmissions in those aged 75 and older and we have demonstrated that the mean BOOST and LACE scores for those readmitted was significantly higher than those not readmitted. Whilst the multivariate logistic regression model accurately predicted the highest number of cases with 74.5% of correct cases identified and the area under the curve was acceptable, sensitivity and specificity could be improved. Overall the predictive power is not optimal, these tools still hold some value in preventing readmissions. This study shows the strongest predictor of readmission is previous admission, and health literacy. 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 2 tool has the potential to provide a pathway for quality improvement where interventions (such as teach back) based on identified risk factors (i.e. literacy) could help in preventing readmissions.

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.

Declaration of Interests

Nothing to declare.

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Table 1: BOOST and LACE scoring systems:

The BOOST index consisted of eight categories:

1. Problem Medication
2. Prescribed [?] 10 medications, or
3. One of: insulin, anticoagulants, oral hypoglycaemics, dual antiplatelet therapy, digoxin, or narcotics.
4. Psychological
5. Previous PHQ-9 performed, or depression history
6. Principal diagnosis
7. One of: cancer, stroke, DM, COPD, or heart failure
8. Frailty
9. Clinical frailty scale score [?] 5 (Score: ___)
10. Poor health literature
11. Inability to perform 'teach back' for 2/3 of,
12. "What is your main problem?"
13. "What do you need to do after leaving hospital?"

14. "Why is it important that you do this?"
15. Poor Patient support

"Do you have someone to help at home should you need it?"

1. Prior hospitalisation Unplanned admission in past 6 months
2. Palliation
3. Would I be surprised if this patient died in the next year, or
4. 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: Non-emergency (+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)

Table 2

Variable	**No readmission (%) (n = 74)**	**Readmission (%) (n = 36)**	**Total (%) (n = 110)**
Patient demographics	Patient demographics	Patient demographics	Patient demographics
Median age (IQR)	82 (72-92)	83 (73-93)	82 (73-91)
Female	47 (63.5)	21 (58.3)	68 (61.8)
BOOST score and components	BOOST score and components	BOOST score and components	BOOST score and components
BOOST (median ±IQR)	3.0 ±2.0	4.0 ±2.0	4.0 ±1.0
Risk diagnosis	53 (71.6)	31 (86.1)	84 (76.4)
Diabetes mellitus	21 (28.4)	19 (52.8)	40 (36.4)
Cancer	19 (25.7)	8 (22.2)	27 (24.5)
COPD	15 (20.3)	9 (25.0)	24 (21.8)
Heart failure	11 (14.9)	5 (13.9)	16 (14.5)
Stroke	6 (8.1)	5 (13.9)	11 (10.0)
Problem Meds	43 (58.1)	25 (69.4)	68 (61.8)
>9 medications	17 (23.0)	15 (41.7)	32 (29.1)
Oral hypoglycaemics	15 (20.3)	13 (36.1)	28 (25.5)
Anticoagulants	16 (21.6)	6 (16.7)	22 (20.0)
Narcotics	8 (10.8)	6 (16.7)	14 (12.7)
Insulin	3 (4.1)	6 (16.7)	9 (8.2)
Digoxin	4 (5.4)	1 (2.8)	5 (4.5)
Dual antiplatelet therapy	2 (2.7)	3 (8.3)	5 (4.5)
Frailty	38 (51.4)	25 (69.4)	63 (57.3)
Palliative	35 (47.3)	20 (55.6)	55 (50.0)
Recent Hospitalisation	26 (35.1)	26 (72.2)	52 (47.3)
Poor health literacy	19 (25.7)	10 (27.8)	29 (26.4)
Poor patient support	14 (18.9)	6 (16.7)	20 (18.2)
Depression History	7 (9.5)	4 (11.1)	11 (10.0)
LACE index and components	LACE index and components	LACE index and components	LACE index and components
LACE (median ±IQR)	10.0 ±1.0	11.5 ±2.0	12.0 ±2.0
Median (IQR) length of stay score	2 (1 to 3)	2 (0 to 4)	2 (1 to 3)
Emergency admission	74 (100)	36 (100)	110 (100)

Median (IQR) comorbidity index score	5 (5 to 5)	5 (5 to 5)	5 (5 to 5)
Median (IQR) recent attendance score	0 (0 to 1)	1 (0 to 3)	0 (0 to 1)

Table 3

Variable	**Significance**	**Exp(B)**	**95% CI Lower**	**95% CI Upper**
Patient demographics	Patient demographics	Patient demographics	Patient demographics	Patient demographics
Age	.829	.993	.928	1.061
Female	.600	1.243	.551	2.807
BOOST score and components	BOOST score and components	BOOST score and components	BOOST score and components	BOOST score and components
BOOST score	**.006**	1.488	1.123	1.970
Risk diagnosis	.100	2.457	.842	7.171
Diabetes mellitus	**.014**	2.821	1.234	6.448
Cancer	.693	.827	.322	2.124
COPD	.574	1.311	.510	3.368
Heart failure	.892	.924	.295	2.892
Stroke	.348	1.828	.518	6.448
Problem Meds	.253	1.638	.703	3.819
>9 medications	**.045**	2.395	1.018	5.636
Oral hypoglycaemics	.077	2.223	.917	5.388
Anticoagulants	.543	.725	.257	2.044
Narcotics	.391	1.650	.526	5.175
Insulin	**.036**	4.733	1.110	20.181
Digoxin	.542	.500	.054	4.643
Dual antiplatelet therapy	.206	3.273	.522	20.525
Frailty	.075	2.153	.927	5.002
Palliative	.417	1.393	.626	3.101
Recent Hospitalisation	**<.001**	4.800	2.008	11.475
Poor health literacy	.814	1.113	.454	2.729
Poor support	.774	.857	.299	2.454
Depression History	.787	1.196	.327	4.384
LACE index and components	LACE index and components	LACE index and components	LACE index and components	LACE index and components
LACE index	**.003**	1.542	1.159	2.051
Length of stay score	.413	1.172	.801	1.713
Emergency admission	-	-	-	-
Comorbidity index score	.999	28421.103	.000	-
Recent attendance score	**.001**	2.027	1.334	3.078

Table 4

Variable	**Significance**	**Exp(B)**	**95% CI Lower**	**95% CI Upper**
Model 1: BOOST score components and sub-components	Model 1: BOOST score components and sub-components	Model 1: BOOST score components and sub-components	Model 1: BOOST score components and sub-components	Model 1: BOOST score components and sub-components
Risk diagnosis	.248	3.141	.450	21.938
Diabetes mellitus	.611	1.513	.307	7.459
Cancer	.282	.439	.098	1.965
COPD	.958	1.039	.247	4.381
Heart failure	.623	.602	.080	4.545
Stroke	.572	.569	.080	4.034
Problem Meds	.240	.328	.051	2.103
>9 medications	.206	2.627	.587	11.753
Oral hypoglycaemics	.553	1.726	.284	10.497
Anticoagulants	.833	.834	.154	4.514
Narcotics	.825	1.198	.241	5.955
Insulin	.261	3.772	.372	38.235
Digoxin	.353	.267	.016	4.321
Dual antiplatelet therapy	.870	1.322	.047	37.183
Frailty	.356	1.673	.561	4.994
Palliative	.580	.714	.217	2.354
Recent Hospitalisation	**.005**	4.621	1.569	13.615
Poor health literacy	.719	1.247	.373	4.165
Poor support	.705	1.303	.331	5.124
Depression History	.861	1.140	.263	4.932
Model 1 summary: Overall percentage = 71.8%, Nagelkerke R^2 = .308	Model 1 summary: Overall percentage = 71.8%, Nagelkerke R^2 = .308	Model 1 summary: Overall percentage = 71.8%, Nagelkerke R^2 = .308	Model 1 summary: Overall percentage = 71.8%, Nagelkerke R^2 = .308	Model 1 summary: Overall percentage = 71.8%, Nagelkerke R^2 = .308
Model 2: BOOST score components	Model 2: BOOST score components	Model 2: BOOST score components	Model 2: BOOST score components	Model 2: BOOST score components
Problem Meds	.893	.934	.347	2.516
Depression History	.814	1.183	.292	4.798
Risk diagnosis	.179	2.330	.679	8.002
Frailty	.292	1.662	.646	4.271
Poor health literacy	.993	.995	.359	2.762
Poor support	.848	1.122	.347	3.622
Recent Hospitalisation	**.002**	4.394	1.706	11.320
Palliative	.597	.767	.288	2.045
Model 2 summary: Overall percentage = 74.5%, Nagelkerke R^2 = .197	Model 2 summary: Overall percentage = 74.5%, Nagelkerke R^2 = .197	Model 2 summary: Overall percentage = 74.5%, Nagelkerke R^2 = .197	Model 2 summary: Overall percentage = 74.5%, Nagelkerke R^2 = .197	Model 2 summary: Overall percentage = 74.5%, Nagelkerke R^2 = .197

Model 3: LACE index components	Model 3: LACE index components	Model 3: LACE index components	Model 3: LACE index components	Model 3: LACE index components
Length of stay score	.443	1.170	.784	1.746
Emergency admission	-	-	-	-
Comorbidity index score	.999	20586.844	.000	-
Recent attendance score	**.001**	1.992	1.311	3.026
Model 3 summary: Overall percentage = 72.7%, Nagelkerke R^2 = .165	Model 3 summary: Overall percentage = 72.7%, Nagelkerke R^2 = .165	Model 3 summary: Overall percentage = 72.7%, Nagelkerke R^2 = .165	Model 3 summary: Overall percentage = 72.7%, Nagelkerke R^2 = .165	Model 3 summary: Overall percentage = 72.7%, Nagelkerke R^2 = .165

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`Figure 1 - IJCP.pdf` available at https://authorea.com/users/403253/articles/514788-a-prospective-cohort-study-comparing-two-predictor-models-for-30-day-emergency-readmission-in-the-elderly