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RESEARCH

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Assessing the accuracy of the LACE index to predict 30-day readmissions in regional Victoria, Australia

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Abstract

Background Unplanned 30-day hospital readmissions are a key quality indicator and pose a significant burden on health systems. Risk stratification tools such as the LACE index (Length of stay, Acuity of admission, Charlson comorbidity index, Emergency department visits) help identify high-risk patients for targeted interventions. Still, their performance in regional populations is less well understood.

Objective To assess the predictive accuracy of the LACEi for 30-day unplanned readmission or death among adult medical patients discharged from a regional health service in Victoria, Australia.

Methods We conducted a retrospective cohort study of all adult medical patients discharged alive from South West Healthcare in Warrnambool, Victoria, between 1 April 2021 and 31 March 2023. LACEi scores were derived from administrative data. The primary outcome was unplanned readmission or death within 30 days of discharge. Discriminatory performance was evaluated using C-statistics, and odds and hazard ratios were calculated for patients classified as high-risk (LACEi >= 10).

Results Out of 4167 admissions, 360 (8.6%) experienced an unplanned readmission within 30 days. Patients readmitted had longer hospital stays, greater comorbidity burden, and higher LACE scores. Using a standard cut-off of >= 10, the index demonstrated moderate predictive accuracy (C-statistic = 0.69; 95% CI 0.67–0.73), with an adjusted OR of 10.4 (95% CI 8.3–12.6) and HR of 8.5 (95% CI 7.0–11.0). Most readmissions (68.1%) occurred within 14 days of discharge.

Conclusion In this regional cohort, the LACEi demonstrated moderate accuracy in predicting 30-day unplanned readmission or death. Scores >= 10 identified patients at higher risk, supporting its use as a simple, low-resource risk stratification tool. Future research should evaluate LACE-guided interventions to reduce early readmissions.

Keywords LACE index, Readmission, 30-day

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Introduction

Unplanned hospital readmissions within 30 days of discharge remain a persistent challenge for healthcare systems worldwide. They incur substantial costs for the healthcare sector and may increase the likelihood of adverse events, such as hospital-acquired infections (Trang Dang et al. 2024). Thirty-day readmission rates are frequently used as a quality metric, and funders have used this to incentivise or penalise health services with higher rates (Australian 2019). Some readmissions are unavoidable due to the natural course of illness, and a significant proportion are potentially preventable (Eric Alper 2021). These are commonly connected to unresolved clinical issues, medication errors, poor discharge plans, or limited post-discharge support (Auerbach et al. 2016, Walraven et al. 2011). In Australia, it is estimated that 20–25% of hospital readmissions could be avoided, positioning them as a focus for quality improvement efforts (Australian 2019). Globally, readmission rates differ widely among countries, with OECD data showing that 30-day medical readmission rates range from 10% to 20%, depending on the structure of healthcare systems and data collection methods (OECD Health Policy Studies 2020). By understanding the factors leading to representation, clinicians can develop risk-stratification tools and interventions that may predict the risk of readmission, channelling resources into prevention strategies.

Risk factors for readmission

Several factors influence readmission rates, including the healthcare system, geographic location, and patient demographics (Murray et al. 2021). These can broadly be categorised into modifiable and non-modifiable risk factors. Non-modifiable factors, such as demographic characteristics (age, ethnicity and comorbidity burden), contribute to a patient's vulnerability to readmission (Eric Alper 2021). Older adults have an increased risk due to frailty, nutritional deficiencies and declining physiological reserves, while patients with multiple chronic conditions have higher care needs due to the complexity of managing several chronic conditions (Lærum-Onsager et al. 2021). Whilst frailty assessment tools have also been shown to reduce the risk of readmission (Bourriquen et al. 2024), they may over-represent risk in the older population. Socioeconomic factors, such as income and geographical access to healthcare, also impact the risk of readmission due to the cost of travel, access to health services and limited social support networks.

In contrast, modifiable factors provide more direct opportunities for intervention, and health services should aim to identify these areas. These include premature hospital discharges, which lead to inadequate post-discharge care, higher readmission rates, therapeutic errors, medication discrepancies, and complications from procedures or infections (Eric Alper 2021). Breakdowns in communication between healthcare providers and patients can further contribute to insufficient follow-up care, resulting in missed chances for preventive measures and timely interventions (Becker et al. 2021). In a systematic review of 19 randomised clinical trials, communication interventions at discharge were linked to lower readmission rates, better medication adherence, and higher patient satisfaction (Becker et al. 2021). Addressing these issues allows healthcare systems to implement targeted strategies, improving patient outcomes and reducing readmission rates (Chua and Johnson 2022, Staples et al. 2021).

Risk stratification tools

The ability to accurately identify patients at high risk of readmission at the point of discharge is essential for the efficient allocation of transitional care resources. Risk stratification tools are widely used in healthcare to identify high-risk patients with a 30-day readmission risk, enabling practitioners to implement targeted interventions and personalised care plans, thereby improving patient outcomes. These tools also facilitate efficient resource allocation by focusing on high-risk patients, potentially reducing costs and optimising efforts. Commonly used prominent risk-stratification tools to predict the risk of 30-day readmission include the LACE index (LACEi), HOSPITAL score, LACE + and the probability of repeated admission score (PRA) (Walraven et al. 2011, Rajaguru et al. 2022, Sharma et al. 2024). However, clinicians often find it difficult to predict readmission risk accurately based on intuition alone, which highlights the need for objective, validated risk stratification tools (Kansagara et al. 2011).

Among the most widely studied and used tools is the LACEi, originally developed to predict the combined outcome of 30-day unplanned readmission or death in general medical and surgical patients (Walraven et al. 2011). The index includes four readily available administrative variables: Length of stay (L), Acuity of admission (A), Comorbidities (C), and Emergency department visits in the past six months (E) (Walraven et al. 2011, Gruneir et al. 2011). The Charlson Comorbidity Index (CCI) is a component of the LACEi, a scoring system used to predict the risk of mortality associated with comorbidities in medical patients (Charlson et al. 1987, Glasheen et al. 2019). Developed by Charlson et al., the authors assigned weighted scores to various comorbid conditions based on their association with mortality. The index was initially designed to predict one-year mortality in medical patients but has since been adapted for multiple settings, including predicting outcomes in various medical conditions, guiding treatment decisions, and stratifying patients in research studies (Charlson et al. 2022). The LACEi is calculated by assigning points to each component based on predefined criteria, producing a total score ranging from 0 to 19, with higher scores indicating greater risk. A score of 10 or more categorises a patient as high risk for 30-day readmission or death after hospital discharge (Walraven et al. 2011, Rajaguru et al. 2022). The index's simplicity and reliance on routinely collected data make it an attractive option for real-time use at the bedside, although its accuracy may be affected by coding practices (Rajaguru et al. 2022).

However, like many prediction models, the LACEi demonstrates only moderate discrimination. A meta-analysis of 38 studies reported a pooled C-statistic of 0.72, with performance varying considerably across different patient populations and clinical settings (Rajaguru et al. 2022). The index performs better in cohorts with chronic conditions such as heart failure but less well in heterogeneous or surgical populations. Other tools, such as the HOSPITAL score, which incorporates laboratory and administrative variables to identify potentially avoidable readmissions, have shown similar modest performance in comparative studies (Sharma et al. 2024, Donze et al. 2013a).

More recently, advanced machine learning models leveraging large administrative datasets have been developed. International studies comparing machine learning to traditional tools have yielded mixed results, with one study of elderly patients with arrhythmia reporting that a machine learning model more accurately identified one-year heart failure readmission risk than the LACEi (ROC 0.76 vs. 0.59). Despite improved prediction rates, even the machine learning model did not provide substantially better performance than the LACEi (Song et al. 2024, Jencks et al. 2022).

In Australia, validation studies of the LACEi have mainly been carried out in large metropolitan hospitals. These studies have shown C-statistics between 0.58 and 0.64 for specific conditions like chronic obstructive pulmonary disease (Hakim et al. 2017), community-acquired pneumonia (Dobler et al. 2020), and acute myocardial infarction (Labrosciano et al. 2021), with a noticeable gap in regional and rural areas (Dreyer et al. 2024). These communities face unique challenges, such as limited access to specialist services, workforce shortages, longer travel distances to healthcare facilities, and a greater reliance on primary care for post-discharge follow-up. All of these factors could affect readmission rates and how well a prediction tool developed and validated in urban centres performs.

Given these uncertainties, including the suggestion from a previous nested case-control study at the facility that the LACE index could be used in this population (Dreyer et al. 2024). We aimed to investigate its accuracy in a regional setting using a more robust methodology. The present study sought to evaluate the predictive accuracy of the LACE index for 30-day unplanned readmission or death in a cohort of medical patients discharged from a large subregional health service in Victoria, Australia. By employing a whole-cohort design, we aimed to provide a more pragmatic estimate of the performance of the LACEi in the clinical setting.

Aims and objectives

The study aimed to describe the demographic and comorbidity profiles of all medical admissions and develop a profile using the Charlson Comorbidity Index (CCI) and the LACE Index (LACEi). The primary goal was to describe the demographic profile, risk-stratify all-cause medical admissions, and assess the accuracy of the LACEi (cut-off >= 10) (Walraven et al. 2011) in predicting 30-day readmission risk.

Methods and setting

Study design and setting

This retrospective cohort study used administrative data from South West Healthcare (SWH), a multi-campus regional public health service based in the Southwest of Victoria, serving around 110,000 people. Data from all campuses were combined to capture the entire medical patient cohort. The study was conducted from 1 April 2021 to 31 March 2023, including the period of the COVID-19 pandemic. Historical comparisons show that readmission rates during this time remained consistent with pre-pandemic benchmarks.

Participants

All adult patients (>= 18 years) discharged alive from a general medical unit at any SWH campus were eligible. Surgical and obstetric admissions were excluded because they have different care pathways, follow-up procedures, and are not comparable with medical patients. Other exclusions included inter-facility transfers, planned readmissions identified through administrative coding for elective or scheduled procedures, in-hospital deaths during the initial admission, and discharges against medical advice.

Data collection and variables

Data extracted included patient demographics, admission acuity, length of stay, and primary and secondary ICD-10-AM diagnoses. Comorbidities were mapped to the Charlson Comorbidity Index (CCI) using validated algorithms. Emergency department presentations within six months preceding the index admission were also recorded. The LACE index, originally designed to predict the combined outcome of 30-day unplanned readmission or death in general medical and surgical patients, was calculated by summing points for length of stay, admission acuity, comorbidity burden, and recent emergency

Table 1 Baseline characteristics of the study cohort by 30-day readmission status

Characteristic	30-Day Readmission (*n* = 360)	No Readmission (*n* = 3807)	*p*-value
Sex, n (%)			
Male	151 (41.9)	1505 (39.5)	
Female	209 (58.1)	2302 (60.5)	
Age (years), mean (SD)	71.7 (17.9)	69.2 (18.1)	
Age groups, n (%)			
18–49 years	145 (40.2)	1595 (41.9)	
50–59 years	43 (11.9)	466 (12.2)	
60–69 years	47 (13.2)	602 (15.8)	
70–79 years	62 (17.2)	592 (15.6)	
80 + years	63 (17.5)	552 (14.5)	
LOS (days), median (IQR)	3 (1–5)	2 (1–4)	$p < 0.001$

presentations, resulting in scores ranging from 0 to 19. Consistent with previous validation studies, a score of 10 or greater was considered high-risk (Gruneir et al. 2011, Walraven et al. 2011).

Outcomes

The primary outcome was unplanned readmission or death within 30 days of discharge. Deaths were identified via linkage with the Registry of Births, Deaths, and Marriages. Readmissions were considered unplanned if not coded as elective or scheduled. Secondary outcomes included the distribution of LACE index components and the timing of readmission events relative to discharge.

Statistical analysis

Baseline characteristics were summarised using means ± standard deviations or medians with interquartile ranges for continuous variables, and counts with percentages for categorical variables. Group comparisons employed t-tests or Wilcoxon rank-sum tests for continuous variables and chi-square tests for categorical variables, with p-values reported. Predictive performance of the LACE index was assessed using logistic regression adjusted for age and sex, Cox proportional hazards models for time-to-readmission, and receiver operating characteristic (ROC) analysis to calculate the C-statistic. Missing data, which comprised less than 5% of the dataset, were addressed through multiple imputation. Analyses were conducted using Stata version 18.0 (StataCorp, College Station, TX, USA).

Results

During the two-year study period, 4167 medical admissions met the inclusion criteria, of which 360 (8.6%) resulted in unplanned readmission or death within 30 days of discharge.

Table 2 LACE Index Components by 30-Day Readmission Status

LACE Component	30-Day Readmission (*n* = 360)	No Readmission (*n* = 3807)	*p*-value
LOS score, n (%)			$p < 0.001$
1	114 (31.7)	1305 (34.3)	
2	52 (14.4)	707 (18.6)	
3	52 (14.4)	588 (15.4)	
4	76 (21.1)	657 (17.3)	
5	43 (11.9)	328 (8.6)	
7	23 (6.5)	222 (5.8)	
Acuity score, n (%)	360 (100)	3807 (100)	
Charlson Comorbidity Index, n (%)			$p < 0.001$
0	130 (36.1)	1547 (40.6)	
1	44 (12.3)	437 (11.6)	
2	32 (8.8)	540 (13.9)	
3	55 (15.3)	520 (13.7)	
4+	99 (27.5)	763 (20.2)	
ED Visits (score), n (%)			
0	127 (35.3)	1225 (32.2)	
1	121 (33.6)	1295 (34.0)	
2+	112 (31.1)	1287 (33.8)	
LACE Index Category, n (%)			$p < 0.001$
Low-Risk (0–9)	105 (29.2)	2600 (68.3)	
High-Risk (> = 10)	255 (70.8)	1207 (31.7)	

Participant characteristics and readmission

During the two-year study period from 2021 to 2023, a total of 4167 acute medical admissions met the inclusion criteria. Of these, 360 (8.6%) resulted in the primary composite outcome of unplanned readmission or death within 30 days of discharge.

A comparison of baseline characteristics between patients who were readmitted and those with no readmission is shown in Table 1. The readmitted group was older (mean age 71.7 years [SD 17.9] vs. 69.2 years [SD 18.1]) and experienced a significantly longer median index length of stay (LOS) (3 days [IQR 1–5] vs. 2 days [IQR 1–4]; $p < 0.001$). Patients who were readmitted also had a significantly higher burden of comorbidities, indicated by both the number of comorbidities ($p < 0.001$) and the Charlson Comorbidity Index ($p < 0.05$). The distribution of sex and the number of previous ED visits were similar across both groups.

Data presented as number (%), mean (standard deviation [SD]), or median, and interquartile range (IQR)]. LOS, length of stay.

As shown in Table 2, patients who were readmitted had a higher comorbidity burden than those who were not, with a greater proportion having a CCI of > = 3 (42.8% versus 33.9%, $p < 0.05$). This pattern was also seen in the LACE index, where most readmitted patients (70.8%) were classified as high-risk (score > = 10), compared with those not readmitted (70.8% versus 31.7%, $p < 0.001$).

LOS: length of stay; ED: emergency department. Data are presented as n (%). Acuity of admission was classified as urgent or emergent for all patients.

Analysis of readmission timing showed that most events (68.1%, $n=245$) occurred within the first 14 days after discharge, indicating a clear clustering in the early post-discharge period (Fig. 1). Early readmissions within this two-week period were associated with a higher burden of comorbidities compared to those occurring later (≥ 15 days), with a larger proportion of patients readmitted early having a CCI score of 3 or more (42.8% vs. 30.5%, $p<0.05$), and being identified as high-risk by the LACE index (62.3% vs. 51.7%, $p<0.05$).

LACE index performance

The LACE index demonstrated a strong association with readmission risk, with a higher median score observed in readmitted patients (11 [IQR 8–14]) compared to those not readmitted (7 [IQR 5–10]; $p<0.001$). Using the pre-validated cut-off of >=10, 70.8% of readmitted patients were classified as high-risk, versus only 31.7% of those not readmitted ($p<0.001$). This pattern remained consistent across analyses, and after adjusting for age and sex, patients with a LACE index >=10 had significantly higher odds of 30-day readmission (adjusted OR = 10.4, [95%CI 8.3–12.6]; $p<0.001$). Cox proportional hazards regression also indicated an increased hazard of readmission in this group (HR = 8.5, [95%CI 7.0–11.0]; $p<0.05$).

The discriminative ability of the LACE index to predict the primary outcome was moderate, with a C-statistic of 0.69 (95%CI 0.67–0.73). Receiver operating characteristic curve analysis (Fig. 2) showed that the standardised cut-off >=10 was the optimal threshold for balancing sensitivity and specificity in this cohort.

Discussion

In this regional Victorian cohort of medical inpatients, the 30-day unplanned readmission or death rate was 8.6%, lower than many Australian (Australian 2019) and international benchmarks (Rajaguru et al. 2022), while the LACEi showed moderate predictive ability with a C-statistic of 0.69 (95%CI 0.67–0.73), aligning with findings from earlier validations in Australian settings (Hakim et al. 2017, Dobler et al. 2020, Labrosciano et al. 2021). These results provide a useful reference point for non-metropolitan Australia, where post-discharge

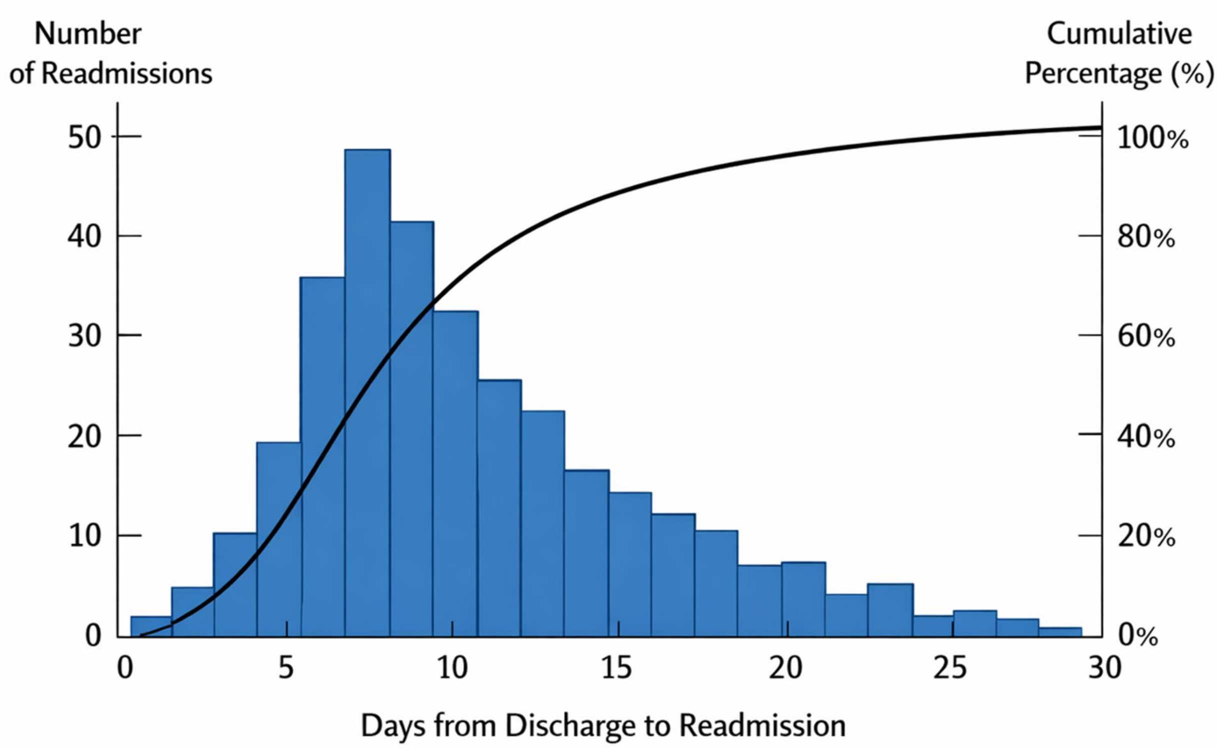

Fig. 1 Distribution of days to unplanned readmission among readmitted patients ($n=360$). Bars represent the number of readmissions occurring on each day following hospital discharge. The solid line represents the cumulative percentage of total readmissions over time

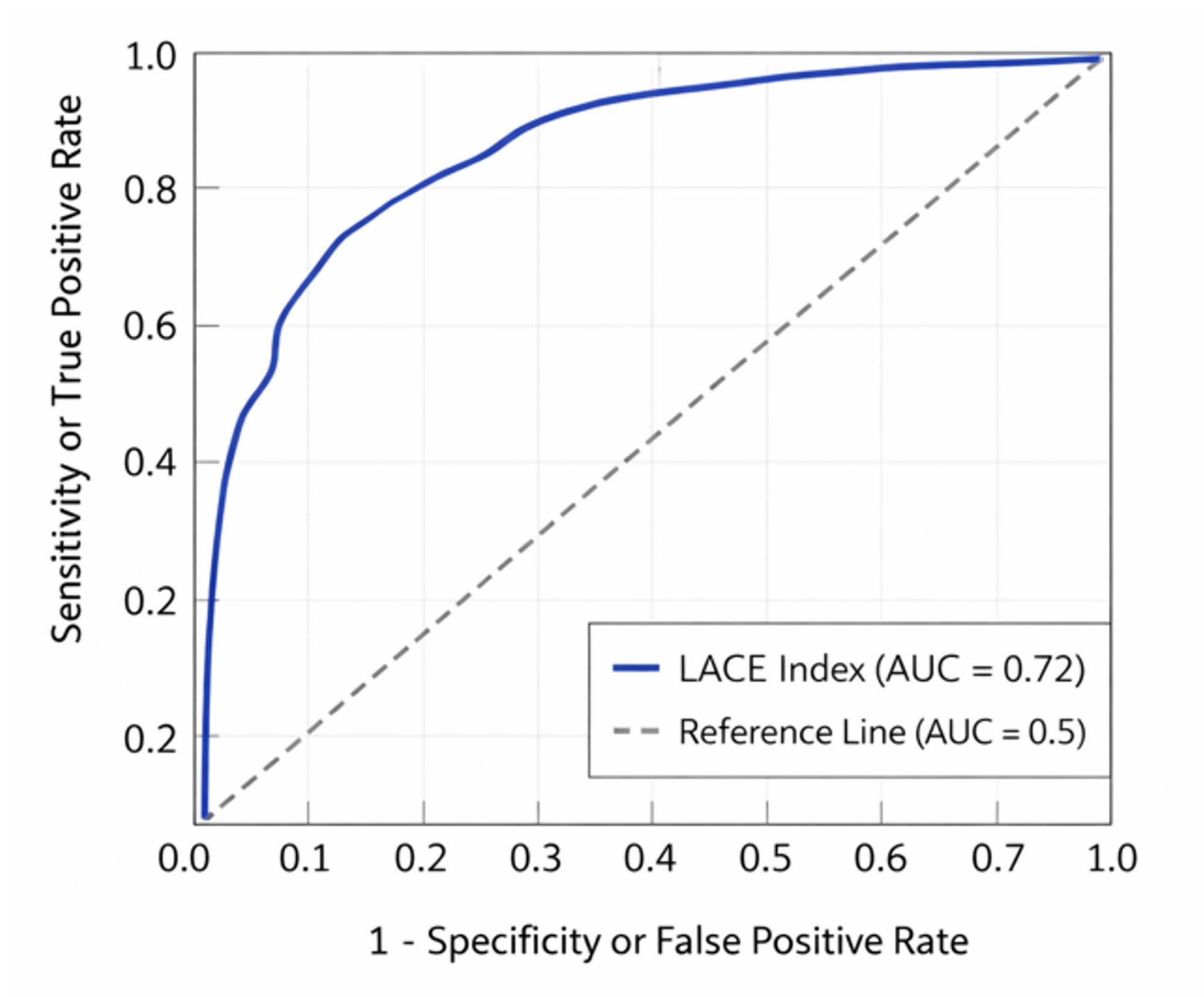

Fig. 2 Receiver Operating Characteristic (ROC) Curve for LACE Index Predicting 30-Day Hospital Readmission. Receiver operating characteristic (ROC) curve demonstrating the discriminative performance of the LACE Index for predicting 30-day hospital readmission

outcomes can vary due to geographic distance, limited specialist services, and staffing challenges (Dreyer et al. 2024).

Comorbidities and readmission risk

Readmitted patients had a longer median index length of stay (3 days versus 2 days, $p<0.001$) and a higher burden of comorbidities, as indicated by greater comorbidity counts and Charlson Comorbidity Index scores. Specifically, 42.8% of readmitted patients had Charlson scores of $>=3$, compared to 30.5% of those not readmitted ($p<0.05$). These findings support well-established evidence that longer hospital stays and multiple chronic conditions increase vulnerability after discharge (Donze et al. 2013b). The increase in readmission rates with longer length of stay reinforces this as a key component of risk stratification and reflects the severity and complexity of the initial admission (Toh et al. 2017, Siddique et al. 2021).

Previous emergency department visits in the past six months showed no significant difference between groups. In regional areas, emergency presentations often result from limited access to primary care rather than solely from acute clinical need, which can reduce the predictive value of this variable compared to urban populations (Gruneir et al. 2011, Dhalla et al. 2014). Most readmissions occurred shortly after discharge, with 68.1% within 14 days, and these early cases were associated with higher comorbidity and LACE scores. This highlights the importance of focusing transitional care on the first two weeks, when modifiable factors may have a greater impact (Kripalani et al. 2014, Kneepkens et al. 2019).

Performance of the LACE index

With the standard threshold of 10, the LACEi demonstrated moderate ability to identify patients at risk of readmission or death, aligning this study's findings with those from international validations. A C-statistic of 0.69 indicates the score correctly ranks the higher-risk patient in 69 out of 100 randomly paired cases. Patients with a LACEi > = 10 had a significantly higher risk of readmission (adjusted OR 10.4, 95% CI 8.3–12.6) and hazard (HR 8.5, 95% CI 7.0–11.0) for the combined outcome of 30-day readmission. Receiver operating characteristic analysis supported a LACEi > = 10 as the optimal cut-off in this cohort, consistent with other large studies (Rajaguru et al. 2022, Fry et al. 2020). Including age and sex added little to the model's performance, confirming that the four core components capture the main predictive information from our cohort's administrative data (Fry et al. 2020).

In Australian studies, earlier work on the LACEi in specific conditions (chronic obstructive pulmonary disease, cardiac disease, community-acquired pneumonia) reported values from 0.58 to 0.64, typically in metropolitan hospitals (Hakim et al. 2017, Dobler et al. 2020, Labrosciano et al. 2021). One study in the same setting reports a C-statistic of 0.59 (Dreyer and Gome 2024); however, this was in a specific cohort, and the influence of the COVID-19 pandemic is unknown. The improved discrimination in the current study may be due to a larger sample size, the inclusion of death as an outcome, the exclusion of surgical patients, or differences in case mix. Collectively, these findings suggest that the LACEi remains a viable option outside major cities, even with regional service limitations.

Comparison with alternative approaches

The HOSPITAL score, which includes discharge diagnoses and laboratory values, often performs as well as or slightly better in specific groups, such as those targeted by readmission reduction programs (Donze et al. 2016). In Australian pneumonia groups, both scores demonstrated similar modest ability to distinguish outcomes (Sharma et al. 2024). The need for laboratory data can make the HOSPITAL score more difficult to use in real-time discharge scenarios in resource-limited settings, while the LACEi relies only on data that are routinely or readily available at the bedside for discharge planning.

Machine learning techniques sometimes give small improvements in discrimination, especially when using detailed electronic health record data (Sharda et al. 2025, Talwar et al. 2023). Tree-based methods like gradient boosting or XGBoost, along with neural networks and deep learning, have achieved C-statistics up to 0.78 in large US hospital networks or heart failure groups, with modest increases over adapted LACE versions (+/- 0.03–0.06 in AUC) in meta-analyses (Sharda et al. 2025, Talwar et al. 2023). However, these benefits are usually limited, vary depending on the machine learning method and population, and seldom lead to large, clinically meaningful differences (Sharda et al. 2025). For regional hospitals, the LACE index remains practically useful because it is based on routinely collected administrative data and is simple to incorporate into discharge workflows.

Strengths and limitations

Strengths include evaluating within a real-world regional context and readmission rates that align with pre-pandemic regional benchmarks despite the COVID-19 study period.

Limitations of the study include its single-centre design, which is confined to a multi-campus setting within a regional health service, thereby limiting the generalisability of the findings to other non-metropolitan services. Furthermore, administrative datasets are susceptible to coding errors and often lack important variables such as social determinants, functional status, and transport barriers, which are particularly relevant in regional populations. Restricting outcome measurement to the index hospital likely resulted in an underestimation of total readmissions, although it remains the main admitting centre in the region. Lastly, as an observational study, causality cannot be confirmed, and LACEi-guided interventions cannot be definitively demonstrated to reduce events.

Implications for practice and future research

These findings support using the LACEi as a practical first-line risk stratification tool in similar regional hospitals, where discharge planning resources are limited. Higher scores may prioritise transitional care interventions such as medication reconciliation, early general practitioner review, and outreach follow-up. The tool should supplement clinical judgement to address factors not recorded in routine datasets. Incorporating automated score calculation into electronic health records may improve consistency and help identify high-risk patients. Future research should evaluate LACE-incorporated care pathways in regional Australian settings through prospective trials assessing readmission outcomes.

Conclusion

This regional Victorian study found that the LACEi demonstrated moderate predictive accuracy (C-statistic = 0.69), and the LACEi > = 10 identified patients with an increased risk of readmission or death (adjusted OR = 10.4; HR = 8.5), with most readmissions occurring within 14 days. These findings support the use of the

LACEi as a simple, low-resource risk stratification tool based on administrative data in regional hospitals. Future research should evaluate LACEi-guided discharge interventions to reduce early readmissions.

Abbreviations

CCI	Charlson Comorbidity Index
ED	Emergency Department
ICD-10-AM	International Classification of Diseases, 10th Revision, Australian Modification
LACE	Length of stay, Acuity of admission, Comorbidity, Emergency visits
LACEi	LACE Index
LOS	Length of Stay
PRA	Probability of Repeated Admission score
SWH	South West Healthcare

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Author contributions
RD conceptualised the study, developed the methodology, and obtained ethics approval. Both RD and PD contributed to data analysis, manuscript drafting, and final submission preparation.

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Data availability
This published article and its supplementary information files contain all data generated or analysed during this study.

Declarations

Ethics approval and consent to participate
The Human Research Ethics Committees at South West Healthcare approved the study and granted a waiver of informed consent (Ref. LNR/76307/SWH-2021-272240). All research adhered to the Australian Code for the Responsible Conduct of Research, along with relevant national legislation and institutional guidelines.

Consent for publication
The HREC granted consent for publication as part of the ethics approval process.

Competing interests
The authors declare no competing interests.

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