LACE Index: Tying Up Loose Ends with Hospital Readmissions

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The Wall Street Journal

Medicare Rules Reshape Hospital Admissions

Health Affairs Blog

Reducing Hospital Readmissions: It's About Improving Patient Care

Besler Consulting

For Fiscal Year (FY) 2015, the Centers for Medicare and Medicaid Services (CMS) has estimated that total readmissions penalties will be approximately $428M, up from $227M in FY 2014.

Modern Healthcare

Most hospitals face 30-day readmissions penalty in fiscal 2016

Cleveland Clinic
Learning Objectives (Pharmacists)

1. Identify independent risk factors for unplanned readmissions
2. Discuss readmission risk prediction models and common pitfalls associated with risk assessment stratification
3. Review primary literature relating to the derivation and validation of the LACE index
Learning Objectives (Technicians)

1. Identify independent risk factors for unplanned readmissions
2. Discuss readmission risk prediction models and common pitfalls associated with risk assessment stratification
Hospital Readmissions: Common & Costly

- **20%** of Medicare patients discharged are readmitted within 30 days
- Estimated annual cost to health care is **$17.4 Billion**
- 2015 national average: **15.2%**

Figure 1. Rates of rehospitalizations within 30 days after hospital discharge
Causes of Hospital Readmissions

- Comorbidities
- Social determinants
- Inpatient care quality
- Health care access
- Post discharge care

Hospitalization

Reasons for Interest

• 30-day hospital readmission rates has become a standard for measuring quality and value
  – Public reporting
  – Financial penalties

• Risk prediction can be used to identify high-risk patients for clinical intervention
  – Re-allocation of health care resources
  – Targeted efforts to improve outcomes
Predictive Analytics

• Analyzes current and historical data using statistical methods to make predictions about the future
• Captures relationships among many factors to allow assessment of risks or opportunities
• Enhances and guides decision-making ability
• Commonly used in actuarial science, marketing, financial services, travel, and health care

Developing Risk Prediction Models

1. Screen patients to identify independent risk factors
2. Apply risk stratification categories (high vs. low risk)
3. Focus health care resources by targeting at risk patients
4. Continual model assessment and validation
Ideal Characteristics of Prediction Models

- Reliable data that are easily obtained
- Deployable in large populations
- Use variables clinically related to and validated in target population
- Good predictive value

- Provide data before discharge
- Discriminate very high from very low risk patients
- Not overly complex
- Adapted to settings and populations in which use is intended

Predictive Analytics Used in Medicine

- ACC/AHA CV Risk Assessment
- APACHE III
- CHADS$_2$
- CHADS$_2$-VAS$_c$

- Framingham 10-Year Risk of CVD
- HAS-BLED Risk Score
- MELD Score
- TIMI Risk Score
Derivation of CHADS$_2$

1994
Atrial Fibrillation Investigators (AFI)

1999
Stroke Prevention in Atrial Fibrillation (SPAF)

2001
CHADS$_2$ index derived by combining risk factors from prior studies and validated in 1773 Medicare patients

CHADS$_2$ Validation
- AFI scheme: c-statistic 0.68
- SPAF scheme: c-statistic 0.74
- CHADS$_2$ index: c-statistic 0.82
Evaluation of Model Prediction

C-Statistic

• Measures model’s ability to discriminate between individuals given predicted risk of an outcome

• Range 0.5 (no better than chance) to 1.0 (perfect)

**C-Statistic Interpretation**

0.5-0.7 → Poor  
0.7-0.8 → Acceptable/ Modest  
>0.8 → Good

Further Development of CHA$_2$DS$_2$-VASc

- **2003**: Framingham score
- **2006**: ACC/AHA/ESC guidelines
- **2006**: National Institute for Health and Clinical Excellence (NICE) guidelines
- **2008**: 8th ACCP guidelines
- **2009**: Birmingham risk stratification schema
- **2010**: Euro Heart Survey on AF
- **2011**: CHA$_2$DS$_2$-VASc score derived by refining Birmingham/NICE schema

**CHA$_2$DS$_2$-VASc Validation**
- CHADS$_2$ index: c-statistic 0.812
- CHA$_2$DS$_2$-VASc score: c-statistic 0.888
Lessons Learned From Clinical Practice

- More data does not equate to more insight
- Ability to interpret data varies based on the data itself
- Predication models should be designed around improving clinical health outcomes
- Developing clinically sound tools takes time and is usually an iterative process
Types of Readmission Risk Models

<table>
<thead>
<tr>
<th>Data Source</th>
<th>Administrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Timing of Data Collection</td>
<td>Retrospective</td>
</tr>
<tr>
<td>Model Category</td>
<td>Retrospective Administrative (14 studies)</td>
</tr>
<tr>
<td>Clinical Utility</td>
<td>POOR Hospital comparisons</td>
</tr>
</tbody>
</table>
### Retrospective Administrative Data

<table>
<thead>
<tr>
<th>Study</th>
<th>CMS CHF Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outcome</td>
<td>30-day readmissions</td>
</tr>
</tbody>
</table>
| Data Source  | • Medicare claims data  
|              | • Index admission and 12 months before index admission |
| Variables    | 37 total, including age, gender, CV variables, and comorbidities |
| Assessment   | C-statistic 0.60 |
## Real-Time Administrative Data

<table>
<thead>
<tr>
<th>Study</th>
<th>Electronic Health Record (EHR) Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outcome</td>
<td>30-day all-cause readmissions</td>
</tr>
</tbody>
</table>
| Data Source | • EHR data from cohort of CHF patients  
|            | • Single urban US center             |
| Variables   | **Social**: address changes, marital status, socio-economic status, anxiety/depression  
|            | **Behavioral**: drug use, missed clinic visits  
|            | **Utilization**: prior admissions, ED presentation time  |
| Assessment  | C-statistic 0.72 (95% CI 0.70-0.75)  |
Types of Readmission Risk Models

- **Data Source**
  - Primary

- **Timing of Data Collection**
  - Retrospective
  - Real-Time

- **Model Category**
  - Retrospective Primary (5 studies)
  - Real-Time Primary (4 studies)

- **Clinical Utility**
  - GOOD: Targeted interventions?
  - POOR: Targeted interventions

## Primary Data Collected in Real-Time

<table>
<thead>
<tr>
<th>Study</th>
<th>Probability of Repeated Admissions (PRA)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Outcome</strong></td>
<td>4-year all-cause readmission</td>
</tr>
<tr>
<td><strong>Data Source</strong></td>
<td>Medicare population (age ≥70) from 1984</td>
</tr>
<tr>
<td><strong>Variables</strong></td>
<td>Age, sex, self-rated health, informal caregiver, coronary disease, diabetes, hospital admission within past year, ≥6 visits within past year</td>
</tr>
<tr>
<td><strong>Assessment</strong></td>
<td>C-statistic 0.6</td>
</tr>
<tr>
<td></td>
<td>Led to development of PRA survey, also with poor predictive ability (c-statistic 0.56-0.61, 95% CI 0.44-0.67)</td>
</tr>
</tbody>
</table>
Patient Variables Evaluated

- **Education**: 0 studies included
- **Caregiver availability or social support**: 2 studies included
- **Access to care**: 5 studies included
- **Socioeconomic status, income, or employment**: 5 studies included
- **Prior hospitalizations**: 14 studies included
- **Medical diagnosis or comorbidity index**: 24 studies included
Literature Conclusions

• Administrative type data is the most common and feasible source to collect patient information from

• Real-time data is more beneficial for making clinical interventions prior to discharge, but depends on the accuracy of actual data collection

• Most prediction models perform poorly, relying on comorbidity and utilization data, while few have examined social determinant variables
LACE Index

Study Design

• Included 11 hospitals (6 university-affiliated, 5 community) in Ontario, Canada

Outcomes Evaluated

• Risk of death or unplanned readmission within 30 days post-discharge

Methods

• Patient interviews pre- and post-discharge, and manual chart review
• Split-sample design to derive and validate an index to predict risk of death or non-elective readmission
Patient Selection

Inclusion Criteria:

• Adult patients
• Discharged from medical or surgical services
• Agree to follow-up telephone call
• Cognitively intact

Exclusion Criteria:

• Nursing home residents
Results

Enrolled
N=5,035

Included
N=4,812

Excluded
- Refused follow-up call (n=124)
- Lost to follow-up (n=83)
- Nursing home admissions (n=16)

Death in first 30 days after discharge (N=36)

Unplanned readmission in first 30 days after discharge (N=349)

## Results – Patient Characteristics

<table>
<thead>
<tr>
<th></th>
<th>Overall no. (%) of patients, n=4,812</th>
<th>Patients without readmission, no. (%) n=4,427 (92.0)</th>
<th>Patients with readmission, no. (%) n=385 (8.0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean age, years (SD)</td>
<td>61.3 (17.0)</td>
<td>61.0 (17.0)</td>
<td>64.7 (16.5)</td>
</tr>
<tr>
<td>Female</td>
<td>2530 (52.6)</td>
<td>2323 (52.5)</td>
<td>207 (53.8)</td>
</tr>
<tr>
<td>Living alone</td>
<td>1127 (23.4)</td>
<td>1033 (23.3)</td>
<td>94 (24.4)</td>
</tr>
<tr>
<td>Charlson comorbidity, median (IQR)</td>
<td>0 (0-0)</td>
<td>0 (0-0)</td>
<td>0 (0-2)</td>
</tr>
<tr>
<td>Prior hospital admissions in previous 6 months, ≥1</td>
<td>1557 (32.4)</td>
<td>1375 (31.1)</td>
<td>182 (47.3)</td>
</tr>
<tr>
<td>Visits to ED in previous 6 months, ≥1</td>
<td>1750 (36.4)</td>
<td>1543 (34.8)</td>
<td>207 (53.8)</td>
</tr>
<tr>
<td>Emergent admission</td>
<td>2796 (58.1)</td>
<td>2505 (56.6)</td>
<td>291 (75.6)</td>
</tr>
<tr>
<td>Length of stay, days, median (IQR)</td>
<td>5 (2-8)</td>
<td>4 (2-8)</td>
<td>7 (4-12)</td>
</tr>
<tr>
<td>Medication count at discharge, median (IQR)</td>
<td>4 (2-7)</td>
<td>4 (2-7)</td>
<td>5 (3-8)</td>
</tr>
</tbody>
</table>
Results – Multivariate Logistic Regression

<table>
<thead>
<tr>
<th>Variable</th>
<th>Odds ratio (95% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length of stay in days</td>
<td>1.47 (1.25-1.73)</td>
</tr>
<tr>
<td>Acute (emergent) admission</td>
<td>1.84 (1.29-2.63)</td>
</tr>
<tr>
<td>Comorbidity (Charlson comorbidity score)</td>
<td>1.21 (1.10-1.33)</td>
</tr>
<tr>
<td>Visits to ED during previous 6 months</td>
<td>1.56 (1.27-1.92)</td>
</tr>
</tbody>
</table>
Scoring Tool

- Derived index score ranging from 0 to 19
- 1-point increase =
  - 18% ↑ odds of unplanned readmissions
  - 29% ↑ odds of early death

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Value</th>
<th>Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length of stay, days</td>
<td>&lt;1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>4-6</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>7-13</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>≥14</td>
<td>7</td>
</tr>
<tr>
<td>Acute (emergent) admission</td>
<td>Yes</td>
<td>3</td>
</tr>
<tr>
<td>Charlson comorbidity score</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>1</td>
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<td>3</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>≥4</td>
<td>5</td>
</tr>
<tr>
<td>Visits to ED, previous 6 mo</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>1</td>
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<td>3</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>≥4</td>
<td>4</td>
</tr>
</tbody>
</table>
Assessment

- Externally validated using 1 million randomly selected patient records

- Moderate discrimination for early death or readmission
  - C-statistic of 0.71 for internal derivation (95% CI 0.67-0.75)
  - C-statistic of 0.68 for external validation (95% CI 0.68-0.69)
LACE Index

- Derived from Canadian patient population with overall low acuity
- Baseline readmission rates were only about 7%
- Model discrimination is better than previous models and has been externally validated
- Each component of the index is readily and reliably determined
- Score can be calculated in real-time during hospitalization
Cleveland Clinic Main Campus

- 1,440 bed, academic medical center
  - Case-mix index > 2.3
- Over 55,000 annual admissions
  - 20-25% admitted through ED
- Average daily census ~1,000 patients
- De-centralized pharmacy model
  - Nursing unit-based and specialist
  - 0700 - 1530 weekdays, consolidated coverage on weekends
Adapting LACE Index Into Clinical Practice

- **Medication count**
  - Active inpatient meds divided by 2

- **High risk medications**
  - Anticoagulants, antiepileptic, diabetic meds, antiarrhythmics (1 point each)

- **Patient age**
  - 65-74 years (1 point), 75+ (2 points)

- **Prior hospitalization**
  - 1 point for each encounter occurring in previous 12 months, up to 4 points

\[ 2x \text{LACE} \]
Weight of Scores

- LACE Score: 59%
- Inpatient Med Count: 29%
- High Risk Med Count: 6%
- Patient Age Points: 6%
Rx High Risk Scoring Tool

• Calculated automatically in real-time for all patients
• Ability to set thresholds that differ by hospital within the health-system
• Minimal correlation with medication history discrepancies
• Score fluctuates throughout inpatient stay
Conclusion

• Growing interest in improving patient care while avoiding financial and reimbursement penalties

• Causes of hospital readmissions are multi-factorial

• Risk stratification and predictive analytics are strategies for better targeting hospital resources

• LACE index provides feasible and accurate model prediction that can be modified for adaptation into clinical practice workflow
Take Away Points

• Relying solely on historical utilization data or clinical factors to predict readmissions may not be the best approach

• Important to consider additional patient-specific variables, such as social determinants

• Leveraging inter-hospital variability can lead to improved clinical event prediction

• Information plus clinical context equals knowledge
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