Use of Novel Predictive Models to Improve Hospital Readmission Program
Presenters

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Agenda and Objectives

Agenda
1) Overview of readmission program
2) Readmission model development process
3) Readmission model results

Learning Objectives
1) Describe the process of integrating EHR and socioeconomic, behavioral, and lifestyle factors behind the hospital’s firewall
2) List the variables that were found to be meaningful
3) Explain the predictive modeling methodology and the similarities and differences with claims-based models

Please ask questions throughout!
Who is UNC Hospitals?

Academic Medical Center in Chapel Hill with outpatient services across North Carolina

- 853 staffed beds (853 licensed)
- >7,800 co-workers
- >1,100 attending physicians
- 780 residents
- >77,000 ED visits
- >30,000 surgeries
- 270,000 inpatient days
- FY15 Net Rev = $1.5B
Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community

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ABSTRACT

Background: Readmissions to hospital are common, costly, and of preventable. An easy-to-use index to quantify the risk of readmission or death after discharge from hospital would help identify patients who might benefit from more intensive post-discharge care. We sought to derive and validate an index to predict the risk of death or unplanned readmission within 30 days after discharge from hospital to the community.

Methods: In a prospective cohort study, 48 patient-level and admission-level variables were collected for 4812 medicare and surgical patients who were discharged to the community from 11 hospitals in Ontario. We used a variable selection strategy to derive and validate an index to predict the risk of death or non-revenue readmission within 30 days after discharge. This index was externally validated using administrative data in a random selective of 1 000 000 Ontarians discharged from hospital between 2004 and 2008.

Results: Of the 4812 participating patients, 815 (0.8%) died or were readmitted on an unplanned basis within 30 days after discharge. Variables independently associated with this outcome from which we derived the nomogram: "LACE" (length of stay [LOS]; acuity of the admission [A], comorbidity of the patient measured with the Charlson comorbidity index score [CC]; and emergency department use (measured as the number of visits in the six months before admission) (E)). Scores using the LACE index ranged from 0 (0.0% expected risk of death or urgent readmission within 30 days to 15 (65.7% expected risk). The LACE index was discriminative in stratifying patients and very accurate (receiver-operator-characteristic [ROC] curve area under the curve (AUC) was 0.70) at predicting outcome.

Interpretation: The LACE index can be used to quantify risk of death or unplanned readmission within 30 days after discharge from hospital. This index can be used with both primary and administrative data. Further research is required to determine whether such quantification changes patient care or outcomes.

Length of stay
Acuity
Charlson comorbidity
Emergency department
Readmission Program Overview

1) Risk modeling initiated with participation in CMS “Community-based Care Transitions Program” (CCTP)

2) Initial model developed for Medicare patients, then expanded to all adult patients
Characteristics of a New Approach

<table>
<thead>
<tr>
<th>Traditional Approach</th>
<th>New Approach</th>
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<tbody>
<tr>
<td>Sicker patients</td>
<td>Riskier patients</td>
</tr>
<tr>
<td>?</td>
<td>Components of risk</td>
</tr>
<tr>
<td>?</td>
<td>Patient experience</td>
</tr>
<tr>
<td>Overall program</td>
<td>Specific program elements</td>
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</tbody>
</table>

Which patients? Sicker patients
Which risk factors? ?
What is changeable? ?
What actually works? Overall program
Powering a Different Approach

Predictive Analytics
- What is likely to happen in the future?

EMR + 3rd Party Data
- What is often associated with bad outcomes?

Clinical + Financial Perspectives
- How do we rationalize fixed resources?

Closed Loop Learning
- How do we iteratively improve?
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Readmission Model: Analytic Plan

Patients
• >18 yo and ≥1 Hospitalization
• 63k patients across 4 years with 4,500 readmits (15%)

Design
• 3 time periods

Time

(1) Pre-Index Hospitalization
(2) Index Hospitalization
(3) Readmit(s)

30-day
90-day
Operational Process

PHI

PII Only

Geo Household Person

PII Only + Consumer Data

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### Readmission Model: Data

- **Consumer data at 3 levels**

1. **Geographic**
   - Census tract, ZIP, ZIP+4, Block group
2. **Household**
   - Street address
3. **Person**
   - Person

<table>
<thead>
<tr>
<th>Socioeconomic</th>
<th>Ethnic distribution</th>
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<tbody>
<tr>
<td>Imputed income</td>
<td>Educational attainment</td>
</tr>
<tr>
<td>Rural/urban</td>
<td>Food desert, etc.</td>
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<tr>
<td>Median age</td>
<td></td>
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</table>

### Consumer Data Levels

<table>
<thead>
<tr>
<th>URL/website categories</th>
<th>Credit risk proxy</th>
<th>Educational attainment</th>
<th>Gambling enthusiast</th>
<th>Health and fitness lifestyle</th>
<th>Traveling and arts interests</th>
<th>Pet ownership</th>
<th>Ethnicity</th>
<th>Plus clothing size</th>
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Data Illustration

• ZIP codes may mask financial stress
Selected Variables From Predictive Model

Higher Risk of Readmission

- More unique inpatient providers in pre-index hospitalization period
- 6 selected diagnoses including endocrine, nutritional and metabolic diseases; pneumonia, complications of procedures
  - Higher blood pressure (Hypertension stage 2)
  - Higher pain intensity reported at prior outpatient visit
  - More unique inpatient providers in pre-index hospitalization period and affordability

Lower Risk of Readmission

- More outpatient encounters in pre-index hospitalization period
  - More provider encounters and education (high school or higher)
  - Diagnosis of hypertension complicating pregnancy childbirth
  - Diagnosis of complications of medical care and education (high school or higher)

Each variable is multiplied by a weighting factor (higher weights in larger font)
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Predictive Model Performance

Evaluated 3 ways:

1) Statistical Performance
2) Clinical Performance
3) Financial Performance
Statistical Performance
Better than our Version 1
Clinical Performance
Better ability of Version 2 to reduce readmissions

At 50% Intervention Impact

<table>
<thead>
<tr>
<th>Category</th>
<th>Readmission</th>
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</thead>
<tbody>
<tr>
<td>Version 1</td>
<td>10%</td>
</tr>
<tr>
<td>Version 2</td>
<td>8%</td>
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Readmissions 2 points or 20% lower

Readmissions as a Function of Program Impact

- V1 New Admit Rate
- V2 New Admit Rate
- Pct Difference

Pct Intervention Impact

- 0% - 10% - 20% - 30% - 40% - 50% - 60% - 70% - 80% - 90% - 100%

Pct Reduction

- -60.0% - -50.0% - -40.0% - -30.0% - -20.0% - -10.0% - 0.0%
Statistical Performance: Claims vs EHR/consumer-based models

Readmission Accuracy Comparison

- EHR and consumer-based better

Readmission Prediction

- C-statistic = 18% higher
- Integrated Discrimination Improvement = 721% higher
Conclusions

1) Readmission program overview
   • Moving from traditional to the “new approach” based on the 4 pillars

2) Readmission model performance
   • Version 2 outperforms LACE and our Version 1 model
     • “Simpler isn’t always better – sometimes better is better”
   • Expected to lead to substantial readmission improvements and improve our economics
Many Thanks!!!!

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Financial Performance
Favorable Impact

Savings across:

1) **Operating Expense**: Availability to double-up or redeploy staff
2) **Gain-share**: New revenue from commercial gain-share contracts
3) **CMS Penalties**: Reduced due to lower readmission rate
4) **Value-based Reimbursement**: Higher margins due to reduced readmissions
Financial Performance
Favorable Impact

Savings Under Value-Based Reimbursement

1) 2,100 beds ≈ 2,515 new patients
   a) 2,515 new patients x $11,000 avg readmission cost = up to $27m gross savings
   b) $27m x 25% readmission program impact = $6.75m
   c) $6.75m - $2.5m new staffing and analytics = $4.25m net savings

2) 210 beds ≈ 252 new patients
   a) 252 new patients x $11,000 avg readmission cost = $2.7m gross savings
   b) $2.7m x 25% readmission program impact = $690k
   c) $2.7m - $250k new staffing and analytics = $440k net savings