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?

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

Statistical Performance

LACE benchmark

Length of stay

Acuity

Charlson comorbidity

Emergency department

CMAJ RESEARCH

Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community

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See related commentary by Goldfield, page 538

ABSTRACT

Background: Readmissions to hospital are common, costly and often preventable. An easy-to-use index to quantify the risk of readmission or death after discharge from hospital would help clinicians 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 medical and surgical patients who were discharged to the community from 11 hospitals in Ontario. We used a split-sample design to derive and validate an index to predict the risk of death or nonelective readmission within 30 days after discharge. This index was externally validated using administrative data in a random selection of 1 000 000 Ontarians discharged from hospital between 2004 and 2008.

Results: Of the 4812 participating patients, 385 (8.0%) died or were readmitted on an unplanned basis within 30 days after discharge. Variables independently associated with this outcome (from which we derived the mnemonic "LACE") included length of stay ("L"); acuity of the admission ("A"); comorbidity of the patient (measured with the Charlson comorbidity index score) ("C"); 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 (2.0% expected risk of death or urgent readmission within 30 days) to 19 (43.7% expected risk). The LACE index was discriminative (C statistic 0.684) and very accurate (Hosmer–Lemeshow goodness-of-fit statistic 14.1, $p = 0.59$) at predicting outcome risk.

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.

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Readmission to hospital and death are adverse patient outcomes that are serious, common and costly. Several studies suggest that focused care after discharge can improve post-discharge outcomes. Being able to accurately predict the risk of poor outcomes after hospital discharge would allow health care workers to focus post-discharge interventions on patients who are at highest risk of poor post-discharge outcomes. Further, policy-makers have expressed interest in either penalizing hospitals with relatively high rates of readmission or rewarding hospitals with relatively low expected rates. To implement this approach, a validated method of standardizing readmission rates is needed.

Two validated models for predicting risk of readmission after hospital discharge have been published. However, these models are impractical to clinicians. Both require area-level information (e.g., neighbourhood socio-economic status and community-specific rates of admission) that is not readily available. Getting this information requires access to detailed tables, thereby making the model impractical. Second, both models are so complex that risk estimates cannot be attained from them without the aid of special software. Although these models have been used by health-system planners in the United Kingdom, we are unaware of any clinicians who use them when preparing patients for hospital discharge.

Our primary objective was to derive and validate a clinically useful index to quantify the risk of early death or unplanned readmission among patients discharged from hospital to the community.

Methods

Study design

We performed a secondary analysis of a multicentre prospective cohort study conducted between October 2002 and July

From the Ottawa Hospital Research Institute (van Walraven, Forster), Ottawa, Ont.; the Institute for Clinical Evaluative Sciences (Austin), Toronto, Ont.; the Department of Medicine (Dhalla, Bell, Etchells), University of Toronto, Toronto, Ont.; the Department of Emergency Medicine (Stiell), University of Ottawa, Ottawa, Ont.; and the University of Calgary (Zarnke), Calgary, Alta.

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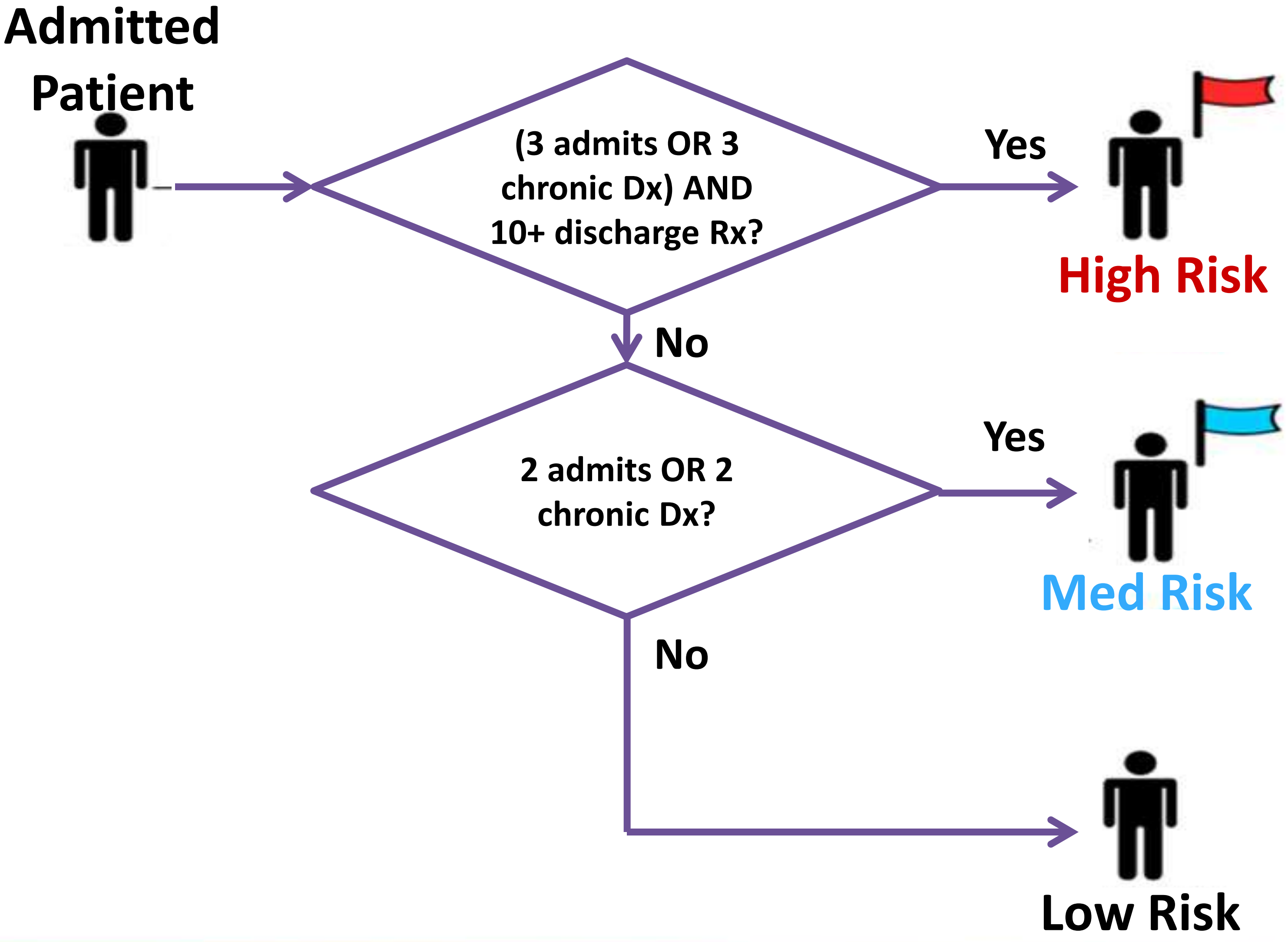
Readmission Program Overview

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

	Traditional Approach	New Approach
Which patients?	Sicker patients	Riskier patients
Which risk factors?	?	Components of risk
What is changeable?	?	Patient experience
What actually works?	Overall program	Specific program elements

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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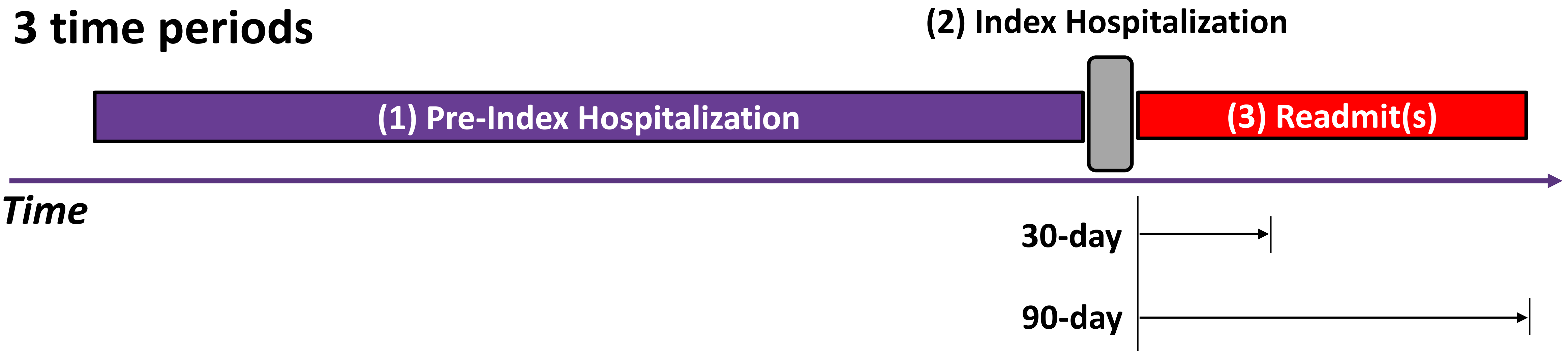
Readmission Model: Analytic Plan

Patients

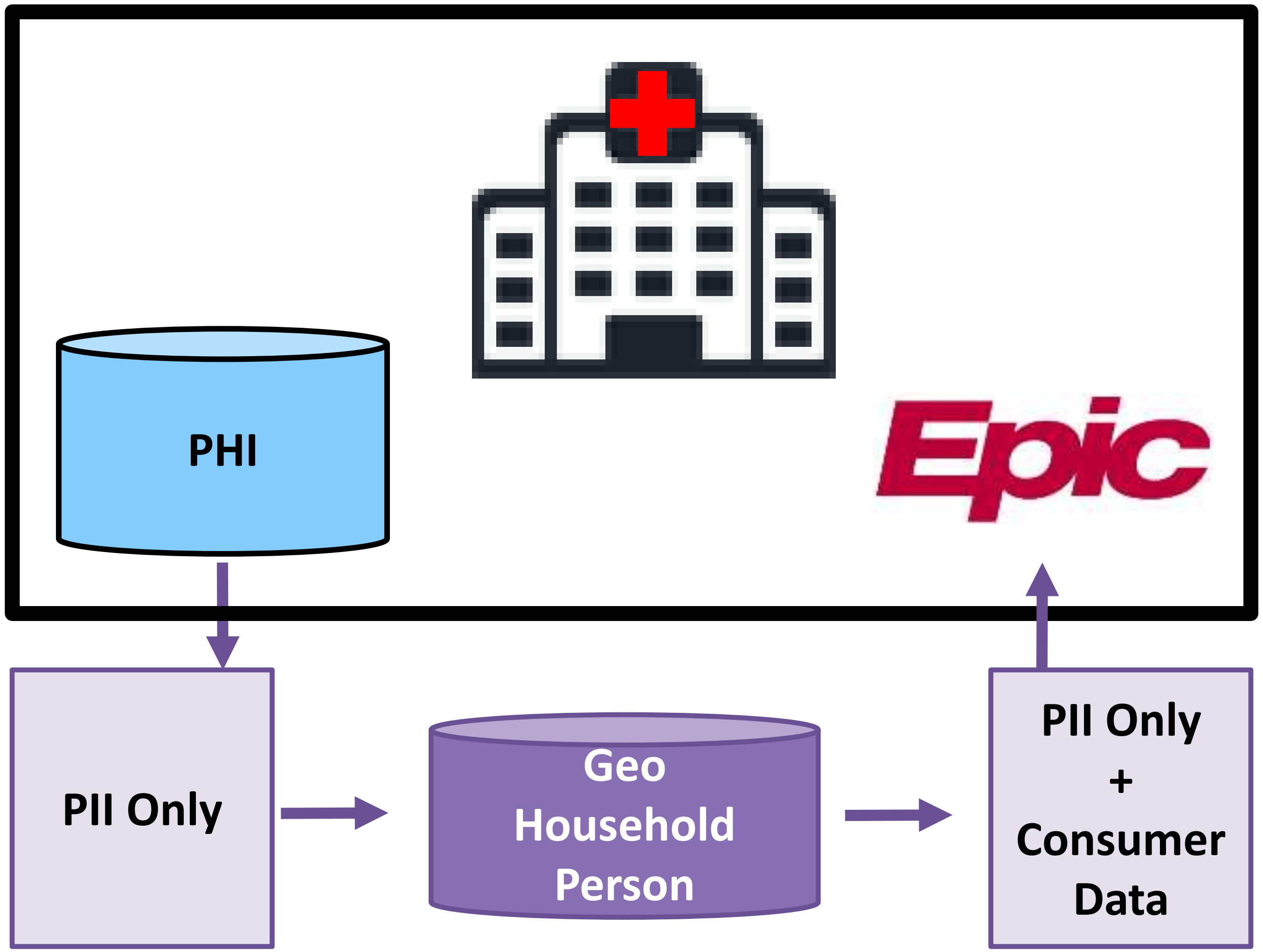
- ≥18 yo and ≥1 Hospitalization
- 63k patients across 4 years with 4,500 readmits (15%)

Design

- 3 time periods



Operational Process



Readmission Model: Data

- **Consumer data at 3 levels**

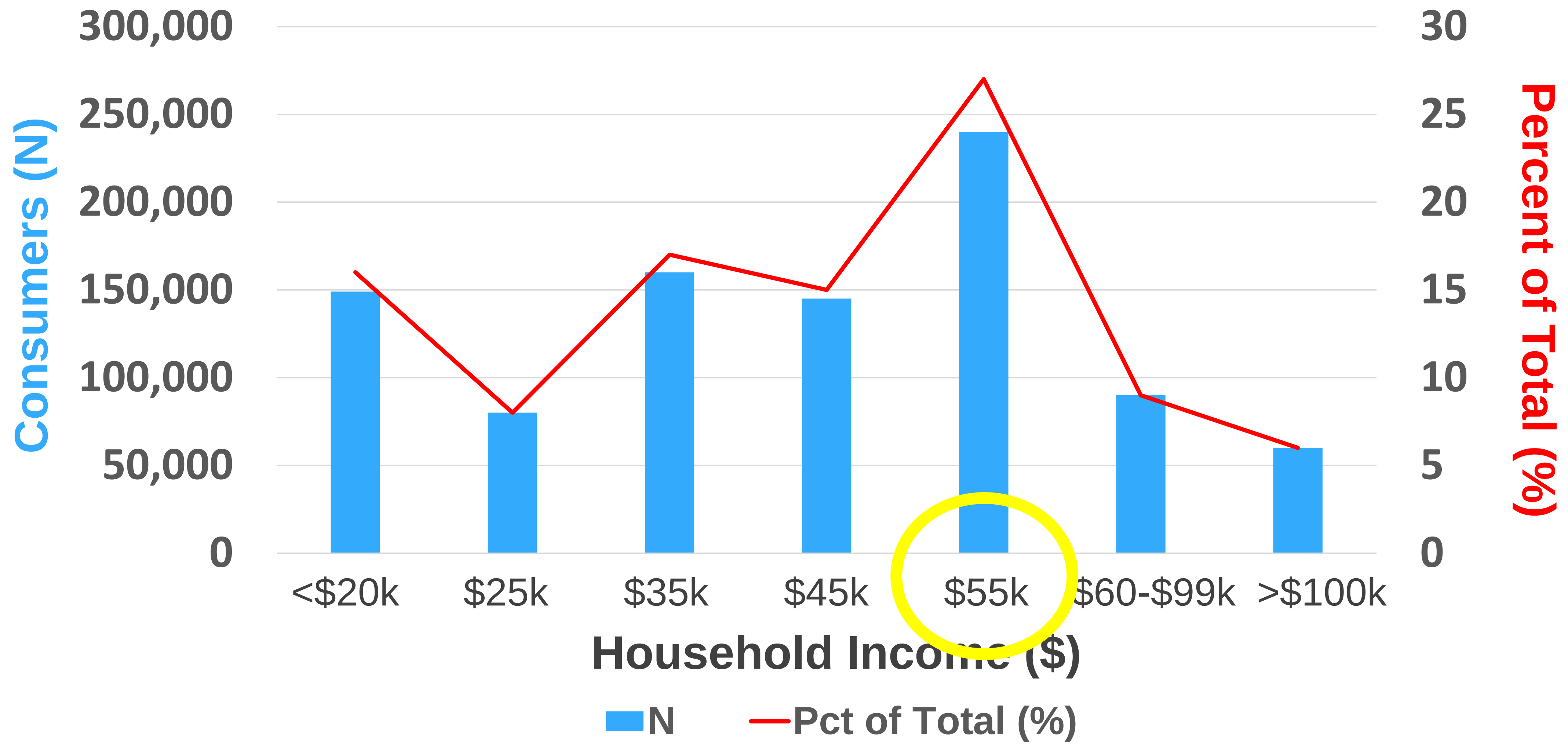
1) **Geographic**
   - **Census tract, ZIP, ZIP+4, Block group**

Socioeconomic
Imputed income
Rural/urban
Median age

Ethnic distribution
Educational attainment
Food desert, etc.

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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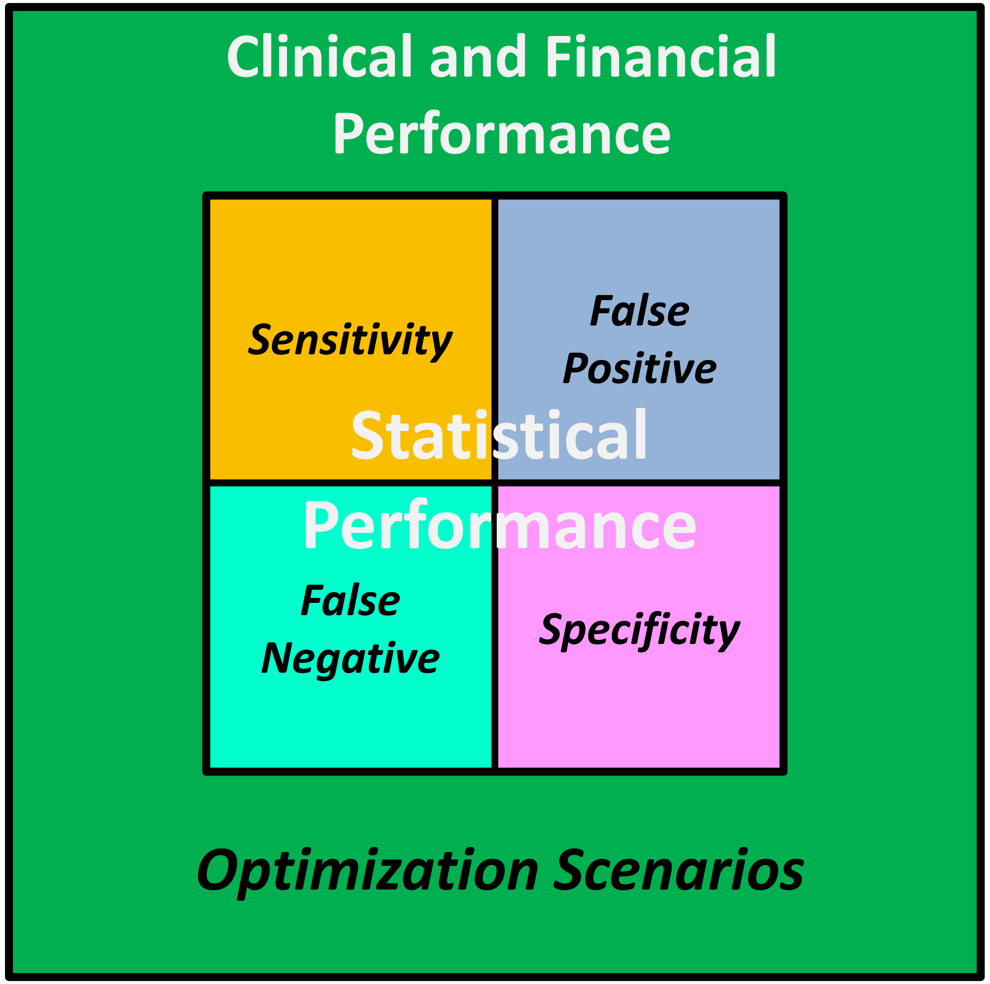
Predictive Model Performance

Evaluated 3 ways:

1) **Statistical Performance**

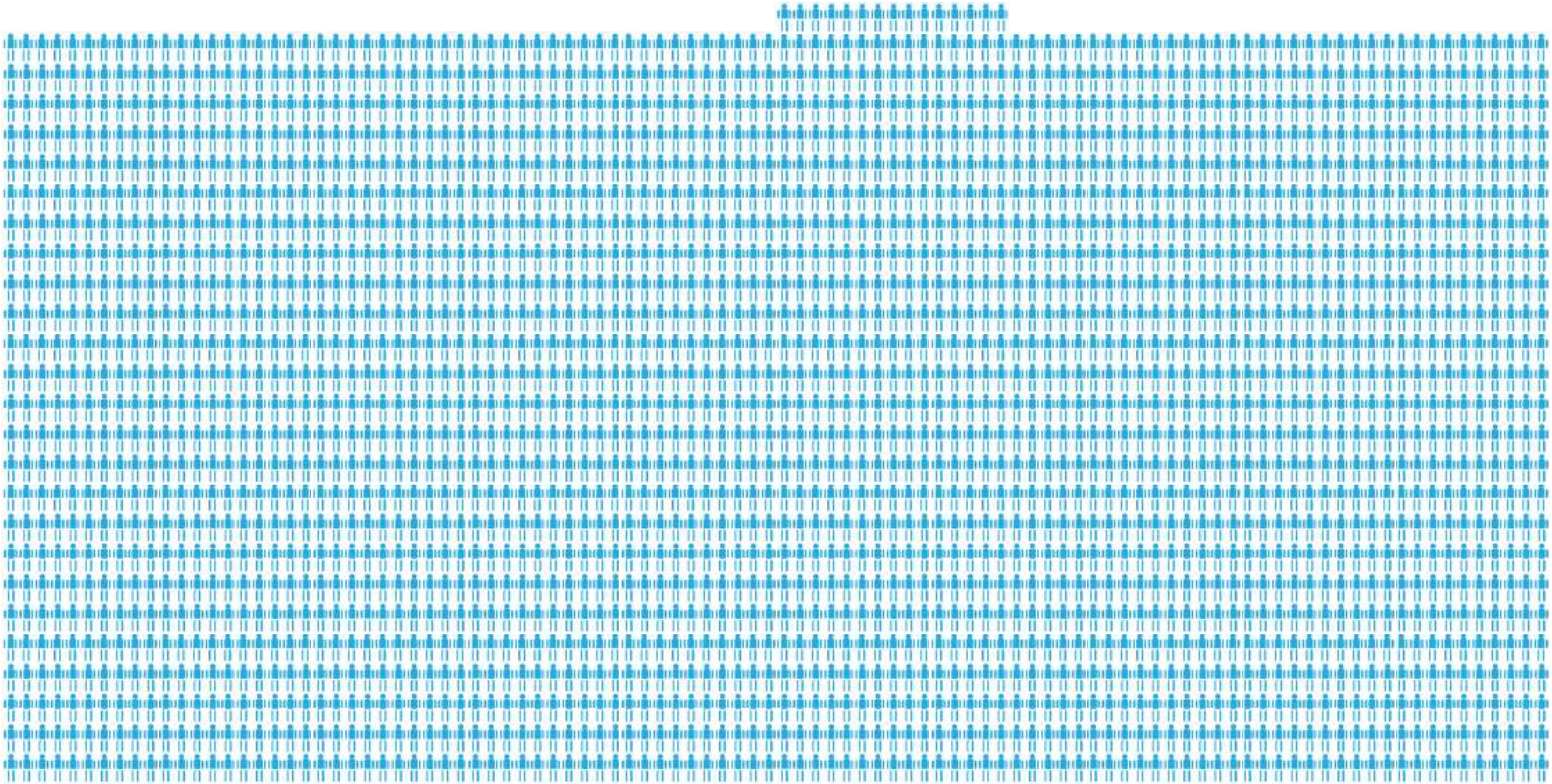
2) **Clinical Performance**

3) **Financial Performance**



Statistical Performance

Better than our Version 1



Clinical Performance

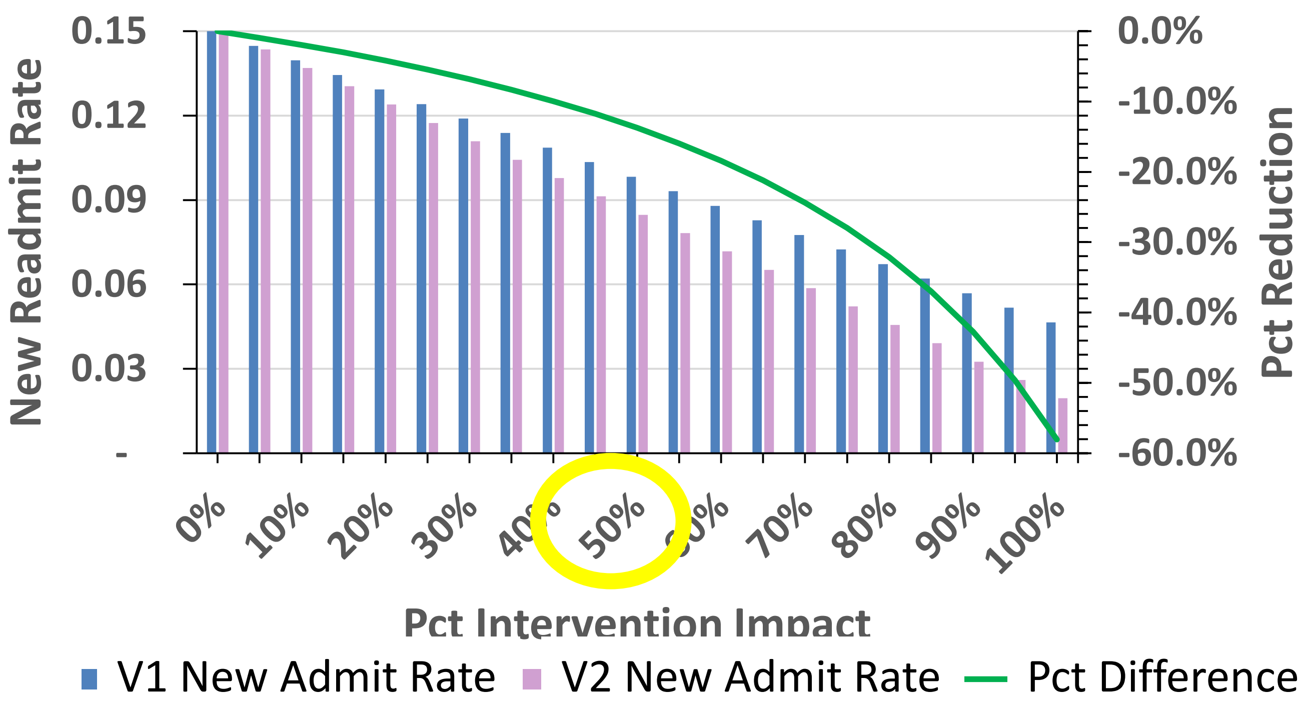
Better ability of Version 2 to reduce readmissions

At 50% Intervention Impact

Category	Readmission
Version 1	10%
Version 2	8%

Readmissions 2 points or 20% lower

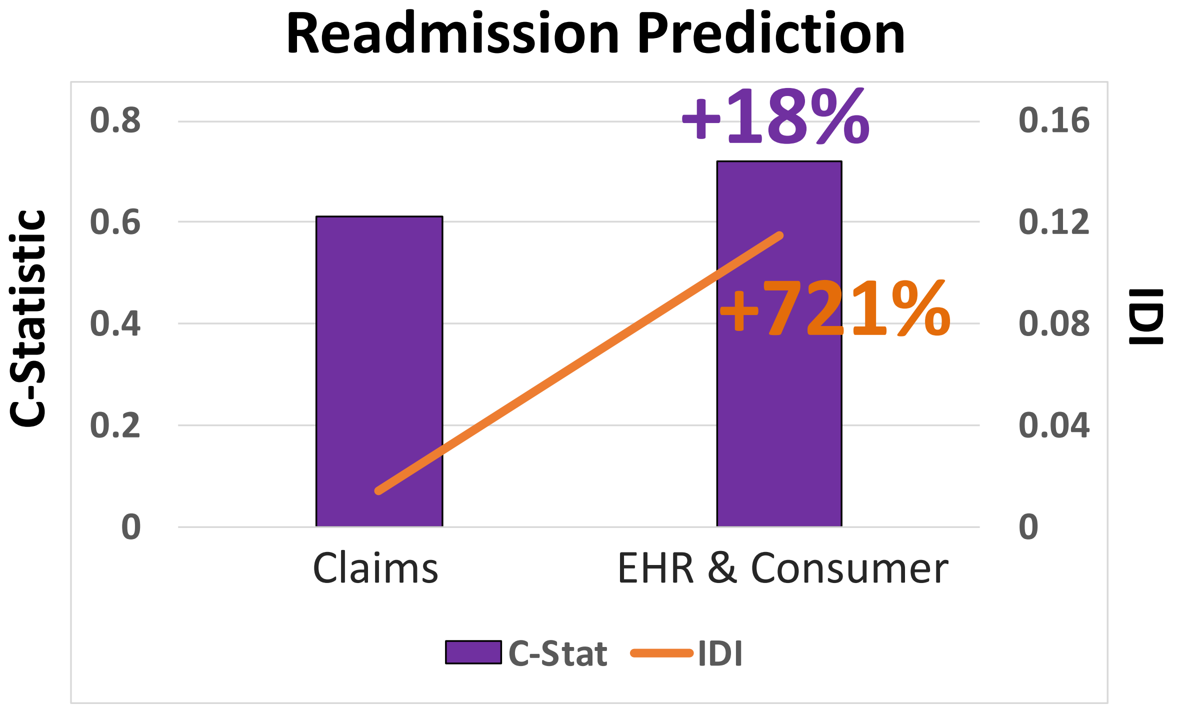
Readmissions as a Function of Program Impact



Statistical Performance:
Claims vs EHR/consumer-based models

Readmission Accuracy Comparison

- EHR and consumer-based better



- 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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