Predicting High Cost Users of Ontario's Healthcare System

Health Analytics Branch
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Ontario

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Introduction

- High cost users (HCUs) are patients who incur the highest costs to healthcare
- The top 5% of users account for 68% of healthcare costs (FY 2010/11)
- Studying high cost users is important for:
  - Improving health outcomes
  - Effectively managing HCUs
  - Providing appropriate care
  - Allocating resources appropriately
  - Easing fiscal pressures on healthcare

Introduction

- A predictive model is a statistical model that uses information on characteristics of units to predict a future outcome (for those units)
- We can use predictive modelling to predict who would become an HCU in the future, using various demographic, SES, clinical, and utilization information
- A Model that predicts who will become an HCU in the future can help:
  - Forecast expenditures and manage budgets appropriately
  - Implement proactive healthcare to prevent patients from becoming HCUs
  - Reduce resource use/impact/cost of HCUs

Methodology

- Purpose of our predictive model:
  - To predict who will / will not become an HCU in the immediate future year, given various patient-level characteristics in the current year and two previous years
- Study period:
  - Model will estimate HCU status among patients from FY 10/11 using patient characteristics from FY 07/08 - FY 09/10
  - Model is validated by applying it to patient characteristics from FY 06/07 - FY 08/09 to predict HCU status in FY 09/10 (out of sample prediction power)
- Statistical technique:
  - Logistic regression model

Methodology

- Step 1: Select the population scope
  - All Ontario residents that are serviced by the health care system in Ontario during FY 09/10 in one of the following care types (database in brackets):
    - Physician services – OHIP (CHDB)
    - Acute care – AIP (DAD)
    - Day surgery – DS (NACRS)
    - Emergency – ER (NACRS)
    - Complex continuing care – CCC (CCRS)
    - Rehabilitation – Rehab (NRS)
    - Inpatient mental health – MH (OMHRS)
    - Long-term care – LTC (CCRS)
    - Home care – HC (HCD)
    - Dialysis – (NACRS)
    - Oncology – (NACRS)
    - Outpatient clinic – (NACRS)

Methodology

- Step 1: Select the population scope (Cont.)
  - Exclusions:
    - Patients who die during the FY 09/10
    - Patients who are under 5 years of age in FY 09/10
    - WSIB claims
    - Telemedicine claims

Methodology

- Step 2: Prepare the data
  - Identify potentially relevant variables for predicting HCUs from corpus of healthcare databases
  - Filter and extract data from various databases (e.g., remove duplicates, select only most updated record for an assessment)
  - Create rules for resolving discrepancies (e.g., conflicting postal codes, records with overlapping assessment periods)
  - Merge all data (care-specific databases, RPDB, PCCF+, etc)
  - Derive predictor variables (e.g., visit count variables, clinical group variables)
  - Transform continuous variables (e.g., on a log scale, or to a categorical variable) if necessary
  - Reduce levels for a categorical variable through clustering
  - Impute missing values using multiple imputation
  - Reduce number of variables (e.g., identify co-linearity, cluster related variables, screen out redundant and irrelevant variables)

Methodology

- Step 3: Identify HCUs
  - High users: the top 5% cost incurring users in FY 10/11
  - Procedure:

1. Sum costs across all in-scope care types for each user
   a) Patient cost for AIP, ER, DS, Rehab, CCC, MH, and HC are derived from unit cost X weighted volume of services
   b) Cost for OHIP claims are represented by fees approved
   c) Patient cost for LTC are estimated using average cost per patient per day X patient length of stay
   d) Oncology, dialysis, and outpatient clinic costs were not included
2. Sort users in descending order of total expenditures, and classify the top 5% of users as HCUs
3. Create and add a binary variable to the data to identify patients as either HCU or not

Methodology

- Step 4: Create a predictive model
  - Using data, create a statistical regression model that estimates the outcome (HCU or not) using factors (covariates) that may be influencing the outcome, such as:
    - Demographic variables (e.g., age, sex, RIO score)
    - Clinical variables (e.g., ICD-10 based chapters, diabetes, CHF, COPD)
    - SES variables (e.g., deprivation index (material and social deprivation))
    - Utilization variables for all care types from current year and previous two years, to account for disease progression (e.g., Number of visits, length of stay)
  - Execute model in SAS

Methodology

- Step 4: Create a predictive model (Cont.)
  - Measure the performance of the model using:
    - Model goodness-of -fit (e.g., AIC criterion)
    - Predictive ability of model for current year (e.g., c statistic)
    - Significance and impact of parameter estimates (e.g., p-value, standardized estimates)

Methodology

- Step 5: Evaluate the predictive power of the model
  - Apply model to FY 06/07–FY 08/09 data to predict HCU status of each patient in FY 09/10, given knowledge of model covariates, as if HCU status is unknown (out of sample prediction power)
  - Measure model performance using:
    - Specificity and sensitivity, positive and negative predictive value, accuracy
      - Select the top 1%, 5%, 10%, 15%, etc. of patients with the highest risk of becoming HCU
    - Receiver operating characteristic (ROC) curve
    - Calibration (goodness-of-fit) curve
  - If necessary, recalibrate model to ensure that the model does not overfit or underfit

Results

- Population of patients: 10,300,856
- Number of HCUs: 520,492 (5% of population)
- Number of variables in initial model: 97
- Variables that were transformed: 64
- Number of variables reduced due to clustering: 28
- Number of variables in final model: 69

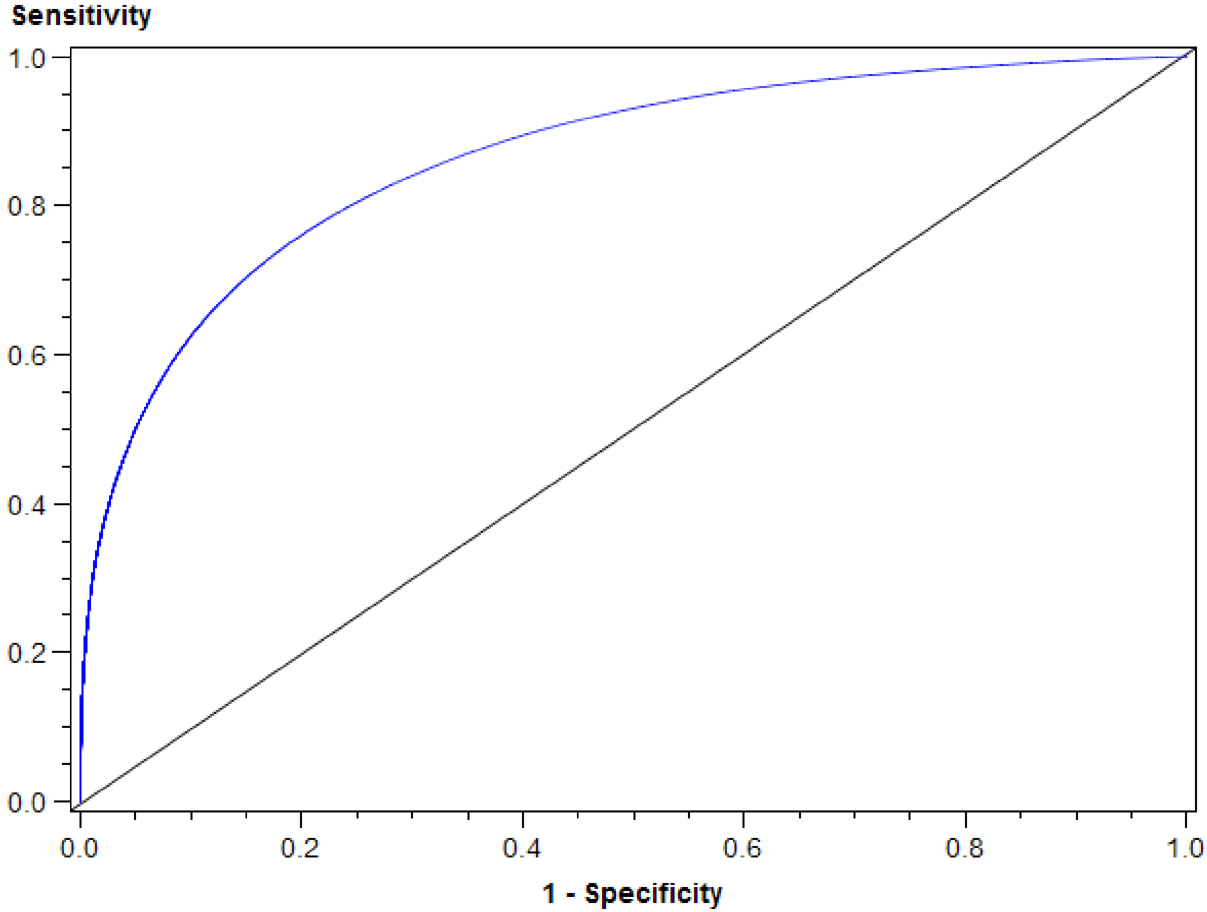
Results

- Performance of model:
  - **C statistic: 0.865**
  - Percent Concordant: 86.1
  - Percent Discordant: 13.0
  - Percent tied: 0.9
- Predictive (out-of-sample) performance of model:

Metric	Selection of patients based on predicted probabilities – the top:				Formula	Notes
	1%	5%	10%	15%		
Sensitivity	15.8%	42.2%	57.1%	66.4%	TP/(TP+FN)	picks up % of all high users
Specificity	99.8%	97.0%	92.5%	87.7%	TN/(FP+TN)	correctly identifies % of those who are not high users
Positive Predictive Value	79.9%	42.6%	28.8%	22.4%	TP/(TP+FP)	good at confirming high users
Negative Predictive Value	95.7%	96.9%	97.6%	98.0%	TN/(FN+TN)	reassuring that a patient will not become a high user
Accuracy	95.5%	94.2%	90.7%	86.7%	(TP+TN)/(P+N)	% of true positive and true negative out of all patients

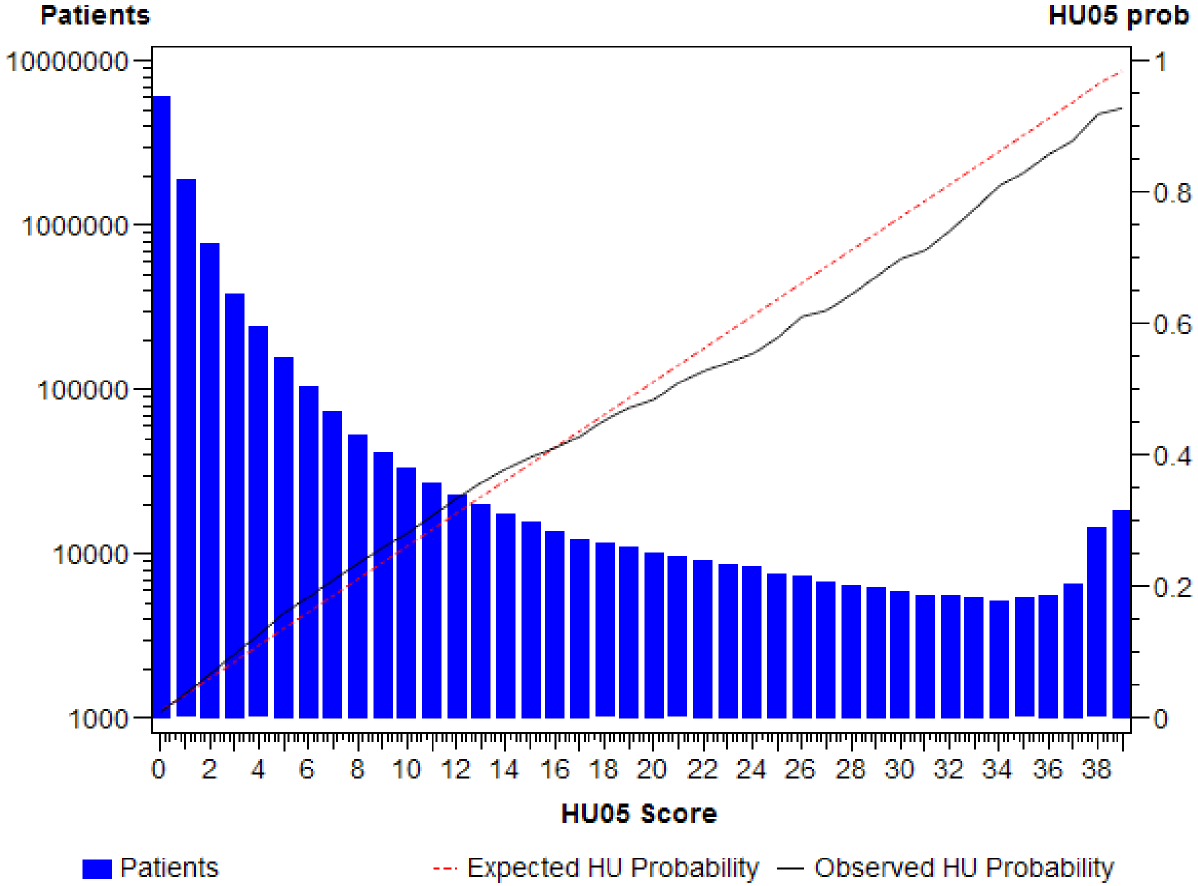
Results

Receiver Operating Characteristic (ROC) plot of model performance on scored 2008 data



Results

Goodness of fit (calibration) curve on scored 2008 data



Discussion

- Example of a patient who has a high probability of becoming an HCU:

  Bart lives in a small town in Bruce County. He is a septuagenarian living in his house. Bart has a mental condition, congestive heart failure, arthritis and cataract. All these health issues made him visit ER and his physician several times during the last 3 years. He was hospitalized in acute inpatient hospital twice 3 years ago. Bart has been supported at home by various homecare services during the past 3 years. Bart's chance of becoming high cost user in the next year is about 80%.

Discussion

- Highlights
  - Very strong (in sample) performance (c = 0.865)
  - Graphs show very strong out-of-sample performance
  - Sensitivity/specificity analysis shows good predictive power
- Limitations
  - No population based case-mix groupers are accessible
    - Used ICD-9 and ICD-10 codes to group patients into ICD-10 chapters as a proxy, where available
  - Large number of predictor variables complicates the application of the model

Discussion

- Next steps
  - Look at different definitions of HCUs (1%, 10%)
  - Model on senior population only
  - Explore different imputation methodologies
  - Use population-based case mix groupers when accessible
  - Look at ways to reduce number of inputs into model
  - Add granularity to homecare sectors

Thank You

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