JOHNS HOPKINS MEDICINE

POPULATION HEALTH ANALYTICS

An Overview of Predictive Modelling and the Predictive Models in the ACG System

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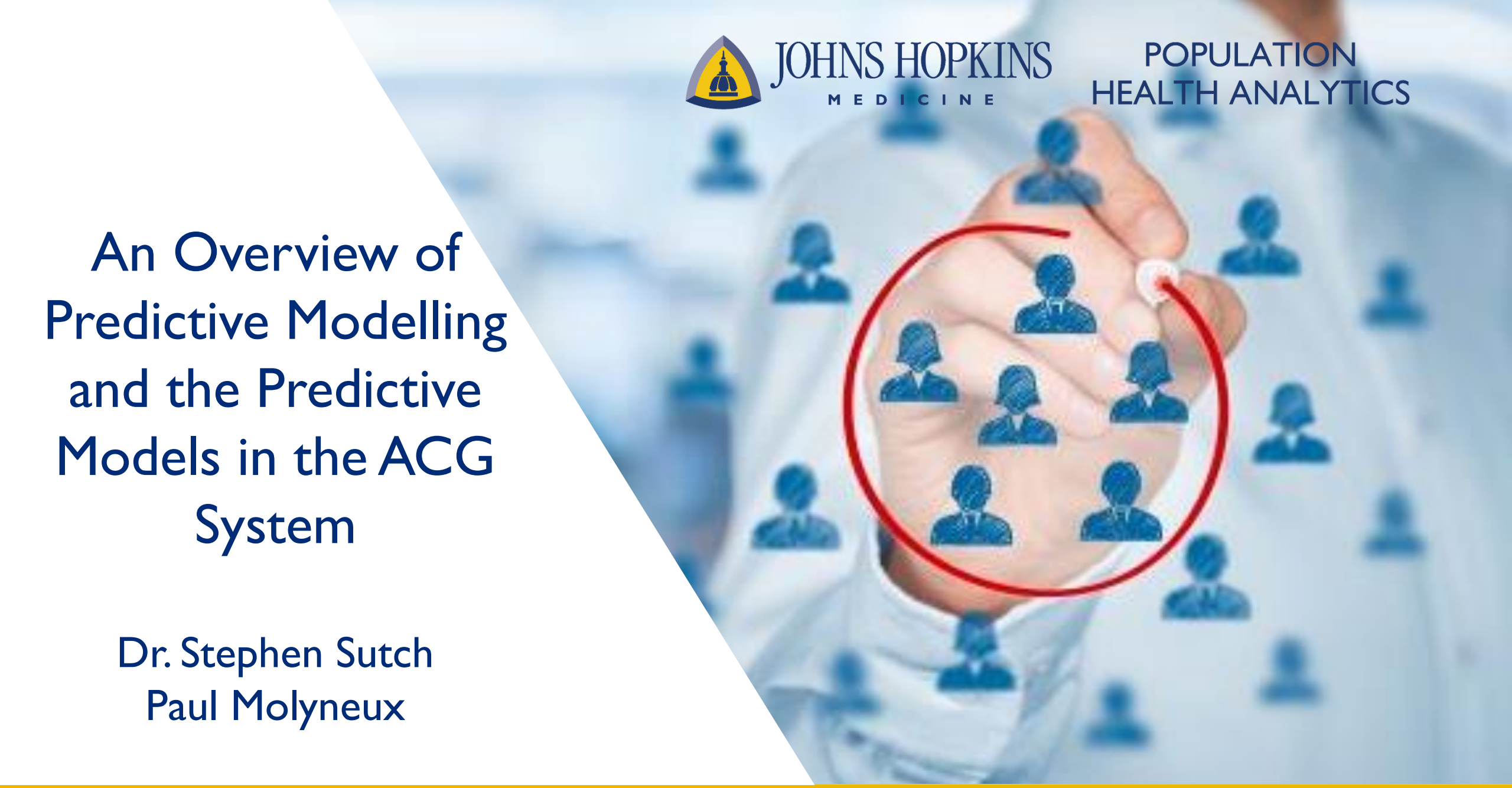


Wednesday, 19 April 2023

AGENDA

- Introductions
- Quick Review previous Webinars
- An Overview of Predictive Modelling and the Predictive Models in the ACG System
- Getting research into practice
- How to Access Recordings and Slides
- Next Session
- Questions & Answers

KEY MARKERS & MODELS IN THE ACG SYSTEM

Main Markers

- Aggregated Diagnostic Groups – ADGs
- Adjusted Clinical Groups – ACGs
- Resource Utilisation Bands – RUBs
- Expanded Diagnosis Clusters – EDCs
- Pharmacy Based Markers – Rx-MGs
- Predictive Models
- Patient Need Groups - PNGs

SUPPLEMENTARY MARKERS IN THE ACG SYSTEM

Supplementary Markers

- Hospital Dominant Condition Marker
- Frailty Markers
- Chronic Condition Count
- Care Coordination Markers
- Condition Markers
- Pharmacy Markers
  - Pharmacy Adherence, Active Ingredient Count, Medicine Management Scores
- Laboratory Markers
- Emergency Department Classification

PATIENT NEED GROUPS: SUMMARY

An **innovative approach** to patient categorization from the Johns Hopkins ACG System

Component 1: Patient Need Groups	Component 2: Care Modifiers	Component 3: Risk Stratification
A core set of 11 population segments	Individual traits with opportunities for clinical intervention	Levels used for insightful overlay of predicted cost with current health needs

PURPOSES OF PREDICTIVE MODELING

- Individual prediction - Individual patients, to improve clinical decision-making and identify candidates for intervention programs (e.g. case management)
- Population predictive models - Groups of patients, to forecast trends (e.g. population profiling) and identify potential areas for healthcare interventions (e.g. DM programs)
- Financial prediction – to anticipate budgetary needs and allocation of resources

PREDICTIVE MODELS FOR RISK STRATIFICATION

- A number of models are available which predict the risk of hospitalisation, from general and insured populations
- Multiple purposes e.g. screening of patients for Case Management Programs, screening for Disease Management Programs, organisational profiling, and assessing financial risk.
- Response to health policies to reduce unnecessary hospital admissions, Pay for Performance (P4P) measures, Risk stratification tool requirements
- A need to support populations in avoiding hospital admissions that are both expensive and a patient safety risk.

METHOD

- The predictive models were derived using patient level data
- Classification of diagnostic, pharmaceutical and historic utilisation data
- Johns Hopkins ACG System helps to reduce the number of variables and provide measures of multimorbidity
- Logistic and Linear Regressions were undertaken to produce models on the outcomes of hospitalisation within 12/6 months, emergency/unplanned hospitalisation within 12 months, and health care expenditures in the preceding 12 months.
- The models were validated using split-half method and providing AUC analyses to compare different model performance.

JOHNS HOPKINS ACG MODELS

- **Concurrent risk**
  - Age-gender
  - Local ACG concurrent
  - Reference ACG concurrent
  - Concurrent risk (regression-based)
- **Predictive cost risk**
  - Predicted cost
  - Rank probability
  - Reference probability
  - Persistent high user
  - High risk unexpected pharmacy cost
- **Hospitalization risk**
  - Inpatient admission
  - Injury
  - Readmission
  - ICU
  - Extended stay

PREDICTIVE MODEL CALIBRATION

- Person-level Data
  - Age, Gender, Dx
    - Medical Services input file has multiple Dx for each person
    - Rx & Expenditures in Base Year are optional
  - Cost in Prediction Year
- Model Marker Output File
  - File Export menu selection in ACG software
  - Decoding tool to extract 225 model markers
- Statistical Software (e.g. R, SAS, SPSS)
  - Regression analysis tool (e.g. linear regression)
  - Coefficient worksheet

EVALUATING YOUR CUSTOMIZATION AND ADAPTATION

Inspect

- Summary Statistics
- Age-gender Distribution
- Local Concurrent Resource Weights by ACG
- Non-matched Codes Export

Bench-mark

- ADG and RUB Distribution
- Compare SMR Reports with ACG Reference Data

Evaluate

- Concurrent and Prospective R^2 for ACG Predictive Models
- C Statistic, Positive Predictive Value (PPV) for Predictive Scores

2020 UK NHS RECALIBRATION

Linear Models

Predictive Model	Original US R^2 [1]	UK 2013 R^2	UK 2016 R^2	UK 2020 R^2
Total Cost	0.226	0.256	0.271	0.266
Drug Cost (based on total cost markers)	Not available	0.355	0.362	0.405
Drug Cost (based on pharmacy cost markers)			0.550	0.598

Existing Binary Models

Predictive Model	Original US AUC [2]	UK 2013 AUC	UK 2016 AUC	UK 2020 AUC
Any Admission - next 12 months	0.774	0.763	0.780	0.775
Any Admission - next 6 months	0.787	0.782	0.801	0.798
Any Admission – LOS of 12 days or more	Not available	0.901	0.912	0.903
Emergency (unplanned) Admission	Not available	0.773	0.786	0.768

MORTALITY RISK SCORE

TABLE 1. The Mortality Risk Score: An Age-based Point-scoring System

Predictor Variable	Score
Age (for each year above 20 years old)	1
Male subject	3
ADG GROUPS	
Time Limited: Minor	−1
Time Limited: Minor-primary Infections	1
Time Limited: Major	6
Time Limited: Major-primary Infections	6
Allergies	−5
Asthma	2
Likely to Recur: Progressive	6
Chronic Medical: Stable	−2
Chronic Medical: Unstable	8
Chronic Specialty: Stable Orthopedic	−3
Chronic Specialty: Stable Ear, Nose, Throat	−3
Chronic Specialty: Stable Eye	−3
Chronic Specialty: Unstable Orthopedic	−2
Chronic Specialty: Unstable Ear, Nose, Throat	−5
Chronic Specialty: Unstable Eye	−2
Dermatologic	−5
Injuries/Adverse Effects: Major	2
Psychosocial: Time Limited, Minor	2
Psychosocial: Recurrent or Persistent, Stable	1
Psychosocial: Recurrent or Persistent, Unstable	13
Signs/Symptoms: Minor	3
Signs/Symptoms: Uncertain	1
Signs/Symptoms: Major	3
Discretionary	−2
Prevention/Administrative	−2
Malignancy	11
Pregnancy	−4
Dental	2

Appendix A

Illustration of determining Mortality Risk Score for a specific subject

Consider a male subject of age 45 years with diagnoses in the following ADG categories: (i) Time Limited: Minor; (ii) Asthma; (iii) Chronic Medical: Stable; (iv) Psychosocial: Time Limited, Minor.

The value of the score for this subject would be: $(45–20)+3+(-1)+2+(-2)+(2)=25+3-1+2-2+2=29$.

This subject's probability of death within 1 year would be:

$$\frac{\exp(-9.0096+0.0800\times 29)}{1+\exp(-9.0096+0.0800\times 29)}=0.00124 \text{ or } 0.124\%.$$

- Note:

Prob = Odds / 1+Odds

e.g. Odds 1 in 4, prob = ¼ / 1+¼ = 0.2

Austin PC, Walraven Cv. *The mortality risk score and the ADG score: two points-based scoring systems for the Johns Hopkins aggregated diagnosis groups to predict mortality in a general adult population cohort in Ontario, Canada.* Med Care. 2011 Oct;49(10):940-7.

PREDICTIVE MODELLING KLOES

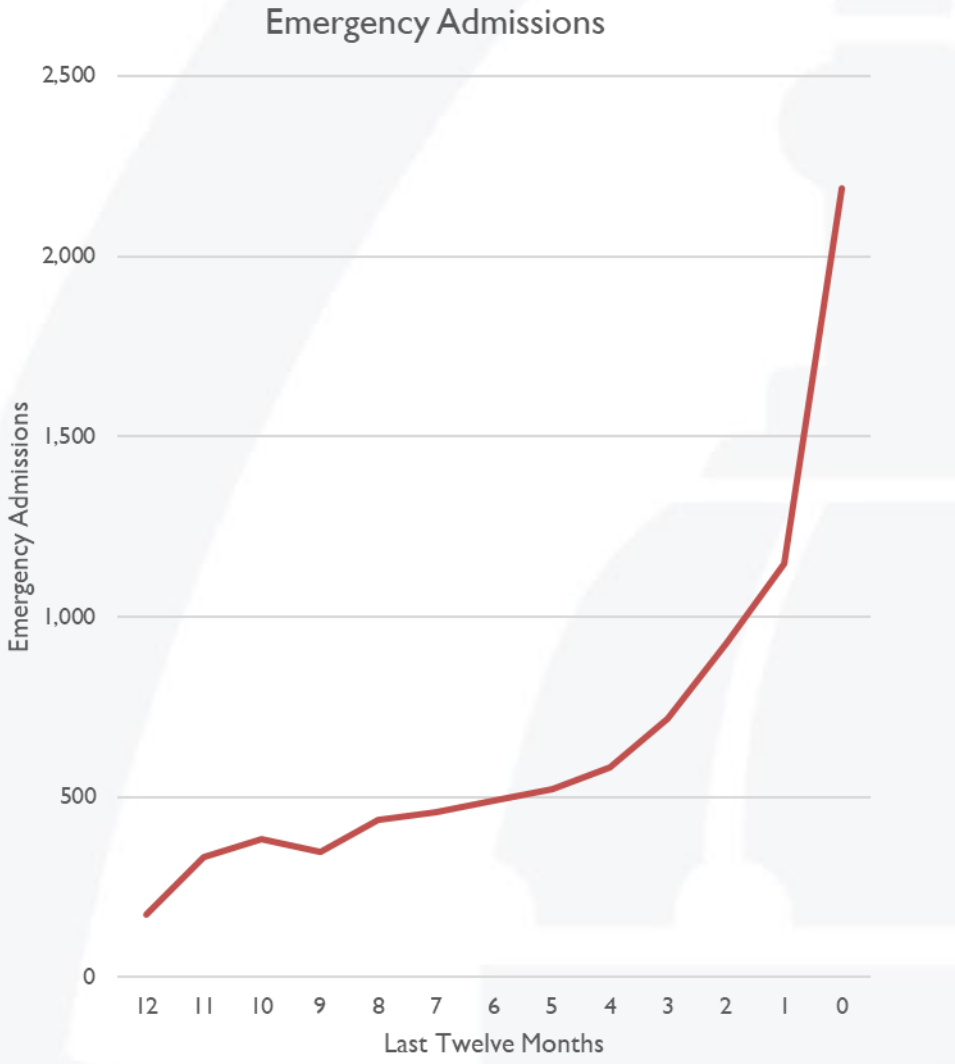
1. Is the outcome you're predicting for negative and actually predictable?
2. Can you do anything to prevent/manage it in a timely manner?
3. Is it making the best use of valuable resources when considering the incidence of the problem and the likelihood of a successful intervention?

Context:

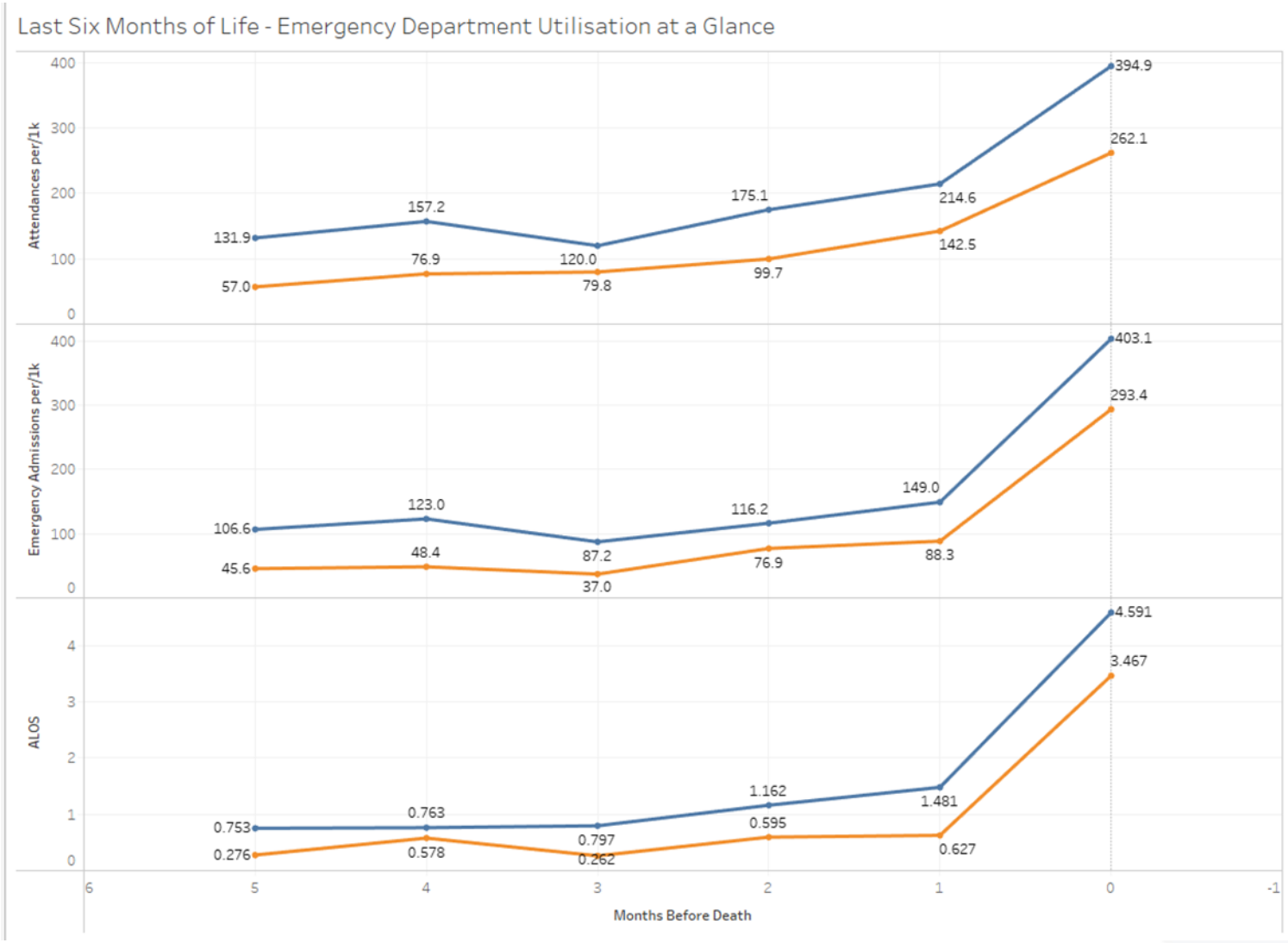
- Dorset residents dying without having been enrolled onto a model of support
- Believed to be very predictable and an issue that scales
- Given the right model of support better outcomes are possible
- Implications for enormous quality, experience and productivity benefits

OPPORTUNITY TO IMPACT

- What typically happens to people in their last twelve months of life?
  - We can gain insight into this by measuring use of healthcare services, in this case emergency admissions (right)
  - For this cohort, more than £14m acute care cost was incurred in the last three months alone
  - More than 43K inpatient bed days
  - This follows a similar pattern when we review A&E attendances
  - It is believed that much of this activity is unnecessary and modifiable



DIFFERENT SUPPORT MODEL | DIFFERENT OUTCOMES



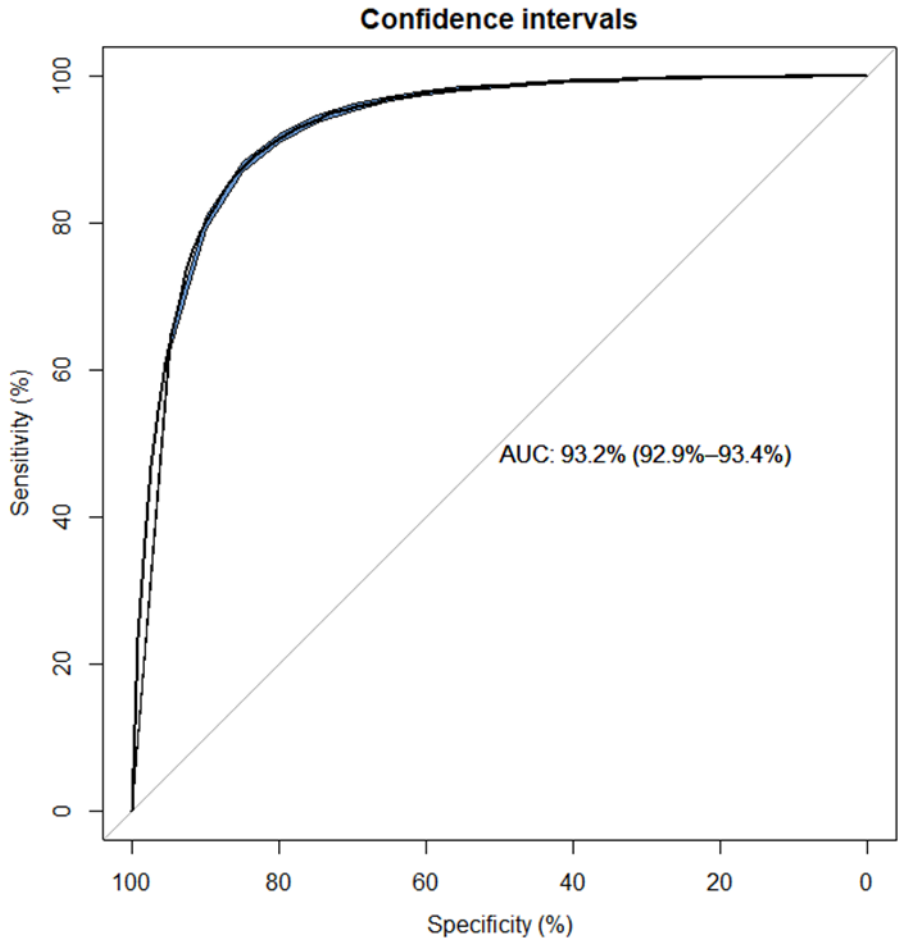
We can plot differences in service utilisation between those identified and enrolled onto a model of support at least six months prior to dying (**orange**) versus those who had not (**blue**).

We estimate that by closing care gaps the following benefits could be realised:

- 600+ fewer A&E visits in the last six months of life (with associated costs of £120k)
- 500+ fewer emergency inpatient admissions (with associated costs of £2m)
- 5,000 potential bed days saved
- 100+ people dying in their preferred place of death

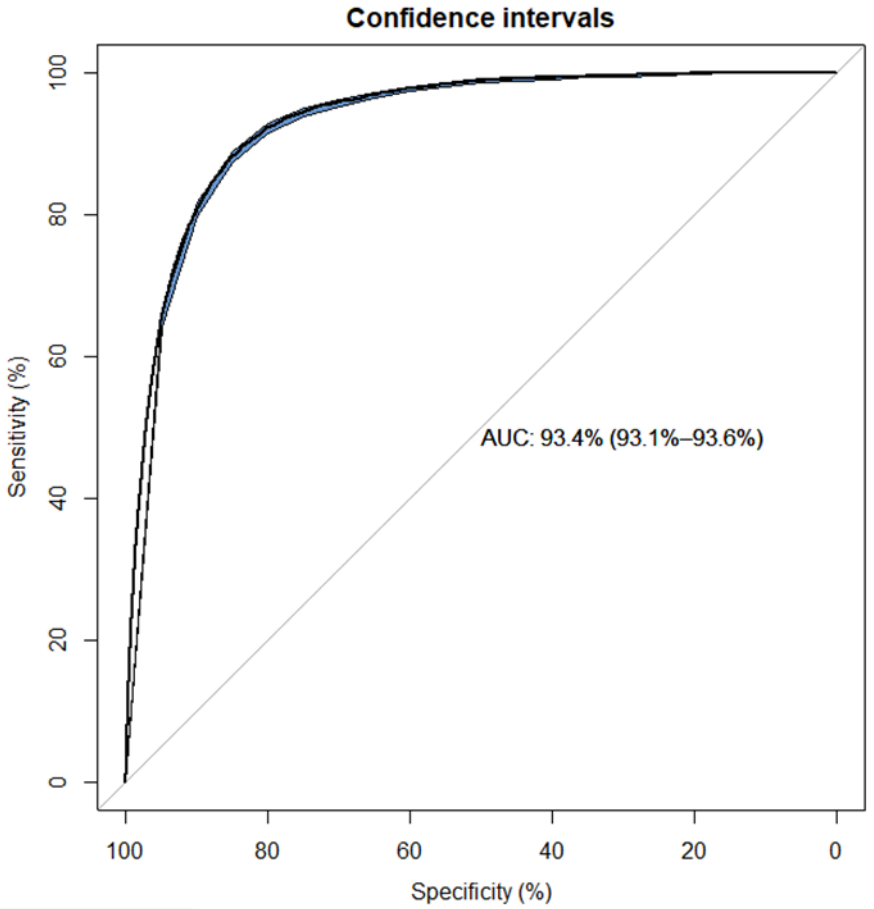
VALIDATION | CALIBRATION | GENERALISABILITY

AS PUBLISHED



- **Accuracy:** **94.9%** | *(0.9488, 0.9498)*
- **Sensitivity:** **62.6%**
- **PPV:** **11.6%**

RECALIBRATED

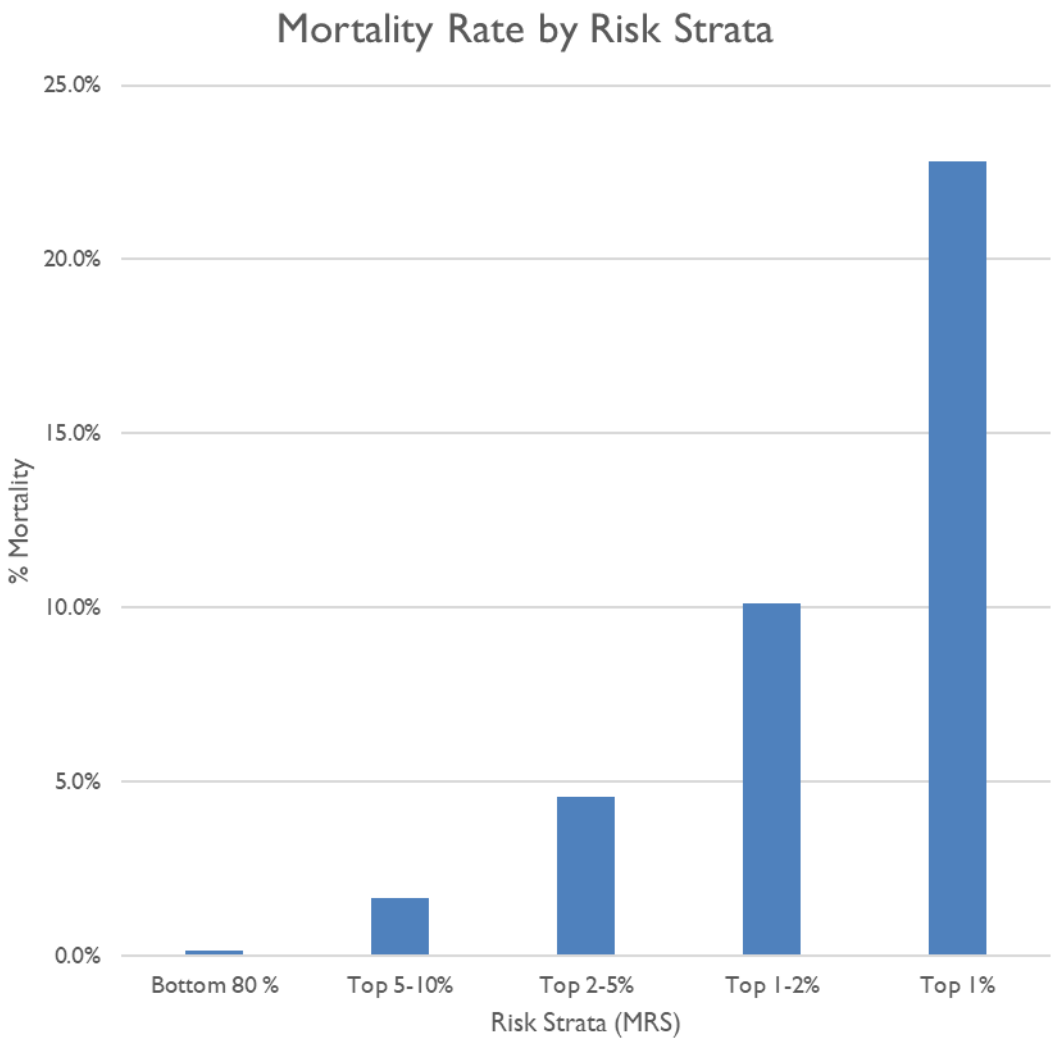


- **Accuracy:** **95.2%** | *(0.9518, 0.9528)*
- **Sensitivity:** **61.6%**
- **PPV:** **12.1%**

RECALIBRATED MODEL

Variable	Description	Estimate
(Intercept)		-10.81426***
Age Group	05-09	0.66698
	10-14	0.54524
	15-19	1.57576
	20-24	2.54912*
	25-29	2.12897*
	30-34	2.81307**
	35-39	3.06281**
	40-44	3.29654**
	45-49	3.66973***
	50-54	3.94263***
	55-59	4.25611***
	60-64	4.70511***
	65-69	5.11896***
	70-74	5.3938***
	75-79	5.7415***
	80-84	6.26145***
	85+	7.07397***
Sex	Male	0.29909***
ADG1	Time Limited: Minor	-0.10289*
ADG2	Time Limited: Minor-Primary Infections	0.3633***
ADG3	Time Limited: Major	0.49725***
ADG4	Time Limited: Major-Primary Infections	0.31774***
ADG5	Allergies	-0.40664*
ADG6	Asthma	-0.04549
ADG7	Likely to Recur: Discrete	0.08956**
ADG8	Likely to Recur: Discrete-Infections	0.08719**
ADG9	Likely to Recur: Progressive	0.20493***
ADG10	Chronic Medical: Stable	-0.02109
ADG11	Chronic Medical: Unstable	0.6274***
ADG12	Chronic Specialty: Stable-Orthopedic	-0.22068***
ADG13	Chronic Specialty: Stable-Ear,Nose,Throat	-0.23585**
ADG14	Chronic Specialty: Stable-Eye	-0.19984***
ADG16	Chronic Specialty: Unstable-Orthopedic	-0.23712*
ADG17	Chronic Specialty: Unstable-Ear,Nose,Throat	-0.5998
ADG18	Chronic Specialty: Unstable-Eye	0.03576
ADG20	Dermatologic	-0.06114
ADG21	Injuries/Adverse Effects: Minor	0.01844
ADG22	Injuries/Adverse Effects: Major	0.30048***
ADG23	Psychosocial: Time Limited, Minor	0.36974***
ADG24	Psychosocial:Recurrent or Persistent,Stable	0.0809**
ADG25	Psychosocial:Recurrent or Persistent,Unstable	0.87852***
ADG26	Signs/Symptoms: Minor	0.11687***
ADG27	Signs/Symptoms: Uncertain	0.31499***
ADG28	Signs/Symptoms: Major	0.41768***
ADG29	Discretionary	-0.12627***
ADG30	See and Reassure	-0.09212.
ADG31	Prevention/Administrative	0.12095*
ADG32	Malignancy	0.65061***
ADG33	Pregnancy	-1.17261*
ADG34	Dental	0.16306

RESEARCH INTO PRACTICE



- People dying without having a plan is bad and represents poor outcomes for both the individual and the system as a whole
- We have demonstrated that this is predictable and can be done at scale using routinely collected data and **ACG markers**
- There are substantial benefits that can be realised if early detection, engagement and management is achieved systematically
- The top 1% most at risk represent a natural and compelling cohort (left)
- Important to review those who have not been enrolled onto a model of support and may be at risk of care coordination issues

Patients With Complex Care Needs: The Hotspotter algorithm

- Hotspotter Definition:
  - Problems in 2 or 3 health domains (chronic physical, mental, social)
  - Multiple acute care visits
- Patient diagnoses over last 12 months (ICPC codes)
- ICPC codes mapped to 32 Aggregated Diagnosis Groups (ADG) using the Johns Hopkins ACG System
- Probability of being a Hotspotter is calculated based on the patient's age, sex, and combination of ADGs

References:
Girwar et al, *Identifying complex patients using Adjusted Clinical Groups risk stratification tool*. Am J Manag Care. 2022 Apr 1;28(4):e140-e145. doi: 10.37765/ajmc.2022.88867. PMID: 35420752.
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https://www.ncbi.nlm.nih.gov/pubmed/21963153

Predictor	Odds Ratio
Age 12-34 year	1.107
Age 35-54 year	1.168
Age 55-69 year	0.936
Age 70-79 year	1.242
Age 80+ year	1.090
Sex (M=1)	1.047
1 Time Limited: Minor	0.918
2 Time Limited: Minor-Primary Infections	1.296
3 Time Limited: Major	2.372
4 Time Limited: Major-Primary Infections	1.247
5 Allergies	0.894
6 Asthma	1.783
7 Likely to Recur: Discrete	1.028
8 Likely to Recur: Discrete-Infections	1.276
9 Likely to Recur: Progressive	1.907
10 Chronic Medical: Stable	2.778
11 Chronic Medical: Unstable	2.886
12 Chronic Specialty: Stable-Orthopedic	1.080
13 Chronic Specialty: Stable-Ear, Nose, Throat	1.154
14 Chronic Specialty: Stable-Eye	1.324
16 Chronic Specialty: Unstable-Orthopedic	1.191
17 Chronic Specialty: Unstable-Ear, Nose, Throat	1.327
18 Chronic Specialty: Unstable-Eye	1.576
20 Dermatologic	0.731
21 Injuries/Adverse Effects: Minor	1.975
22 Injuries/Adverse Effects: Major	2.299
23 Psychosocial: Time Limited, Minor	1.741
24 Psychosocial: Recurrent or Persistent, Stable	3.358
25 Psychosocial: Recurrent or Persistent, Unstable	2.946
26 Signs/Symptoms: Minor	1.628
27 Signs/Symptoms: Uncertain	2.951
28 Signs/Symptoms: Major	1.913
29 Discretionary	1.755
30 See and Reassure	1.177
31 Prevention/Administrative	1.150
32 Malignancy	1.627
33 Pregnancy	1.586
34 Dental	1.406

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Thank You

Questions?

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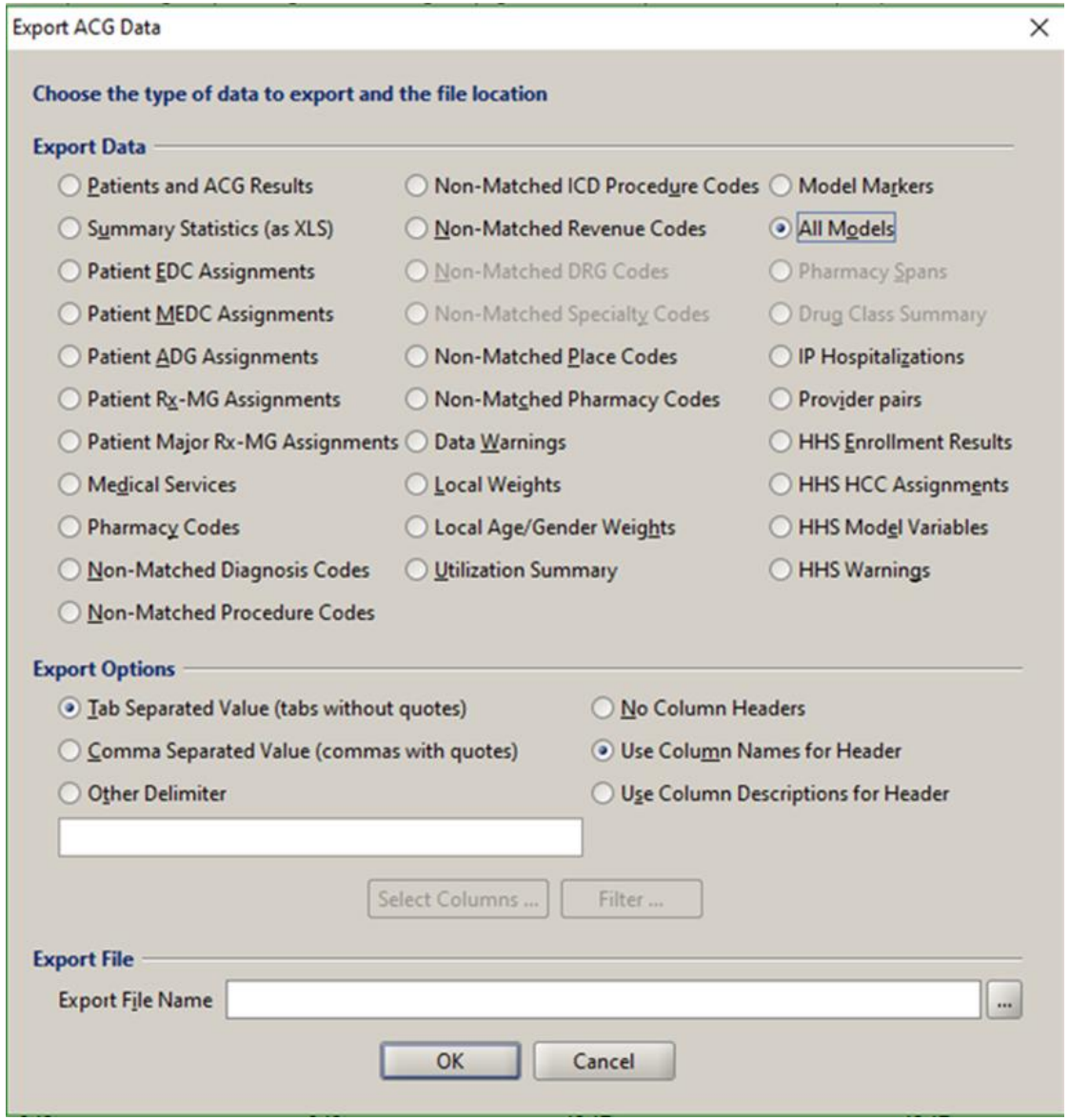
https://www.liebertpub.com/doi/abs/10.1089/pop.2018.0151

MODEL MARKER OUTPUT FILE



- Patient ID
- Demographic Markers – Gender, age bands
- Dx-PM Covariates– Frailty, hospital dominant morbidity types, prospective RUBs, pregnancy w/o delivery, ACG markers, EDC markers
- Rx-PM Covariates – Rx-MG markers
- Cost Percentile Groups – Total cost bands, Rx cost bands
- Utilization markers – Inpatient hospitalizations, outpatient visits, emergency department visits, dialysis services, nursing services, major procedure, cancer treatment.

jhuacg -export MARKERS -acg-file <file> [-delim TAB|COMMA] [col-file <file>] -export-file <file>