



Predictive Models of the Risk of Hospital Admission and Future Healthcare expenditures: The benefits of recalibration

Stephen Sutch DrPH, Klaus Lemke PhD, James Barrett MD
ssutch1@jhu.edu

PCSI Rykayvik, Iceland 29th September 2022

© Copyright 2022 Johns Hopkins University

THE JOHN'S HOPKINS ACG® SYSTEM CELEBRATING DECADES OF IMPACT ON POPULATION HEALTH RESEARCH AND PRACTICE

HopkinsACG.org

AcademyHealth

HealthPartners



1970s

- Prof. Rudman Shufeldt begins early work on children's parents of morbidity leading to the creation of the Aggregated Diagnostic Groups (ADG). *New England Journal of Medicine* 1984;110:624-7 published her article on childhood morbidity.

1980s

- Federal Census develops "ambulatory DRGs".
- Dr. Weiner helps expand pediatric ADGs to adults and helps develop "Ambulatory Case Groups" (now Adjusted Clinical Groups or ACGs).
- *Medical Care* 1981;19:452-72 and *Health Services Research* 1991;26:675-74 publish articles about ambulatory case groups.

1990

- First ACG System is released and shared with other academics.
- ACG System peer-reviewed bibliography goes to press. *Journal of American Medical Association (JAMA)* 1994;271:474-475 published "The case for case-mix adjustment in practice profiling."

1992

- Tech Transfer—Team develops ACG System software for wide-scale dissemination leading to first commercial contract.

1994

- International interest produces first paper in Spanish. *Spain Research* 1994;7:79-82.
- ACG System bibliography grows to over 400 publications.

1996

- First risk adjusted payment—ACG System adopted by Maryland or Minnesota Medicaid programs to allocate more funds to sicker patient populations. Related article published by *Journal Case Manage* 1996;1:20-22.

1997

- Venetian 8 introduced the first ACG System Diagnostic Models pioneered by Dr. Chris Fennel.
- Growing interest in international subjects leads to formation of ACG International Team to support Nordic Countries, Spain, England, and Germany.
- To address this expansion, ACG System was adapted to meet ICD-9 codes.
- First ACG System Live Conference held outside the U.S. in Berlin, Germany.

2003

- With the release of Venetian 8, the ACG System became customizable and adaptable for implementation throughout the world.

2006

- First conferences bring both domestic and international ACG System users together to promote excellence in the application of risk adjustment methods.

2007

- NHE utilization of the ACG System prompts the 1st London Symposium.
- *BMC Health Serv Res* 2007;7:88 published article about predictive modeling in British primary care.

2008

- ACG System implemented in South America and Africa.

2009

- In ACG System Asia Pacific Conference takes place in Kuala Lumpur, Malaysia. *BMC Health Serv Res* 9 (Suppl 3):A7 published article about successful ACG System application in Malaya.
- New ACG System tools support population health management including pharmacy care, outside the hospital/outpatient care, and physician coordination services. Published article in *BMC Health Serv Res* 2009;9:140 highlights ACG System utilization within Johns Hopkins Health System.

2010

- Alliance with World Organization of Family Doctors (WONCA) to contribute to improved delivery of primary care.

2011

- Over 100 publications describe implementation of the ACG System. Hundreds more quickly follow from countries around the world and in numerous languages.

2012

- Contributing the legacy of founding an academy of clinical epidemiology (ACE)—The paper approach for identifying emerging risk in South African populations is presented with the inaugural Shufeldt Award.

2013

- ACG System's New Frontier—the 11th significant ACG System release incorporates new metrics for assessing coordination and patient sharing across clinicians.

2014

- Article published on new analytic approach to case coordination. *J Gen Intern Med* 2013;28:415-416.

2015

- ACG System is awarded the prestigious AcademyHealth Health Services Research (HSR) Impact Award.
- ACG System continues to support healthcare reform in the U.S. *National Health Service Research (NHS)* published article on case finding and risk stratification utilization in the NHS.

THE POPULATION-BASED CASE-MIX SYSTEM WITH THE LARGEST FOOTPRINT IN THE WORLD.





- Clinical 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

Identifying patients for care management

4

- Can occur through multiple methods:
 - referrals by physicians
 - screening statistical algorithms
 - patient surveys
- Increased use of multiple combined approaches to avoid bias in selection by the individual methods

Shadmi & Freund, 2013, *Targeting patients for multimorbid care management interventions: the case for equity in high-risk patient identification*

Example Clinical Process (UK)

5

- Identify at risk patients – ACG risk profiling tool
- Core medical team review
 - Identify problems, Action list, Suitability for further interventions
- Personalised care plan
 - Discussion and delivery of care plan, Coded and scanned to records
- Follow-up
 - Clinical review (named clinician), Date of review, Response to interventions

Source: Cricket Green Medical Practice Model



- 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 MEDICINE POPULATION HEALTH ANALYTICS **ACG RISK 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

7

JOHNS HOPKINS MEDICINE POPULATION HEALTH ANALYTICS **EVALUATING YOUR CUSTOMIZATION AND ADAPTATION**

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



n

Validation Statistics

R-Squared Performance for ACG System Concurrent Risk Models

	R-Squared Modeling Total Cost without Truncation	R-Squared Modeling Total Cost Truncated at \$250,000
Local Age-Gender Risk	0.035	0.056
Local ACG Concurrent Risk	0.229	0.332
Reference ACG Concurrent Risk	0.231	0.333
Concurrent Risk (regression-based)	0.428	0.536

Source: IQVIA, formerly Quantiles/INS, One INS Drive, Plymouth Meeting, PA 19462; Subset of the Legacy PharMetrics Adjudicated Claims Database containing a national cross-section of managed care plans; population of 3,306,768 Commercial beneficiaries (age under 65 years), 2013-15.

Validation Statistics (2)

Expected to Actual Cost Ratios by Cost Quintile for ACG System Concurrent Risk Models

	Local Age-Gender Risk Cost Ratio	Local ACG Concurrent Risk Cost Ratio	Reference ACG Concurrent Risk Cost Ratio	Concurrent Risk (regression-based) Cost Ratio
Top 1%	0.05	0.30	0.30	0.53
Top 5%	0.13	0.46	0.46	0.64
Top 20%	0.31	0.71	0.71	0.81
Mid-High	1.85	1.89	1.89	1.57
Mid	4.43	2.77	2.79	2.07
Low-Mid	11.09	4.22	4.46	3.05
Bottom 20%	271.92	14.73	14.76	21.85

11

11

10/6/2022



JOHNS HOPKINS
MEDICINE

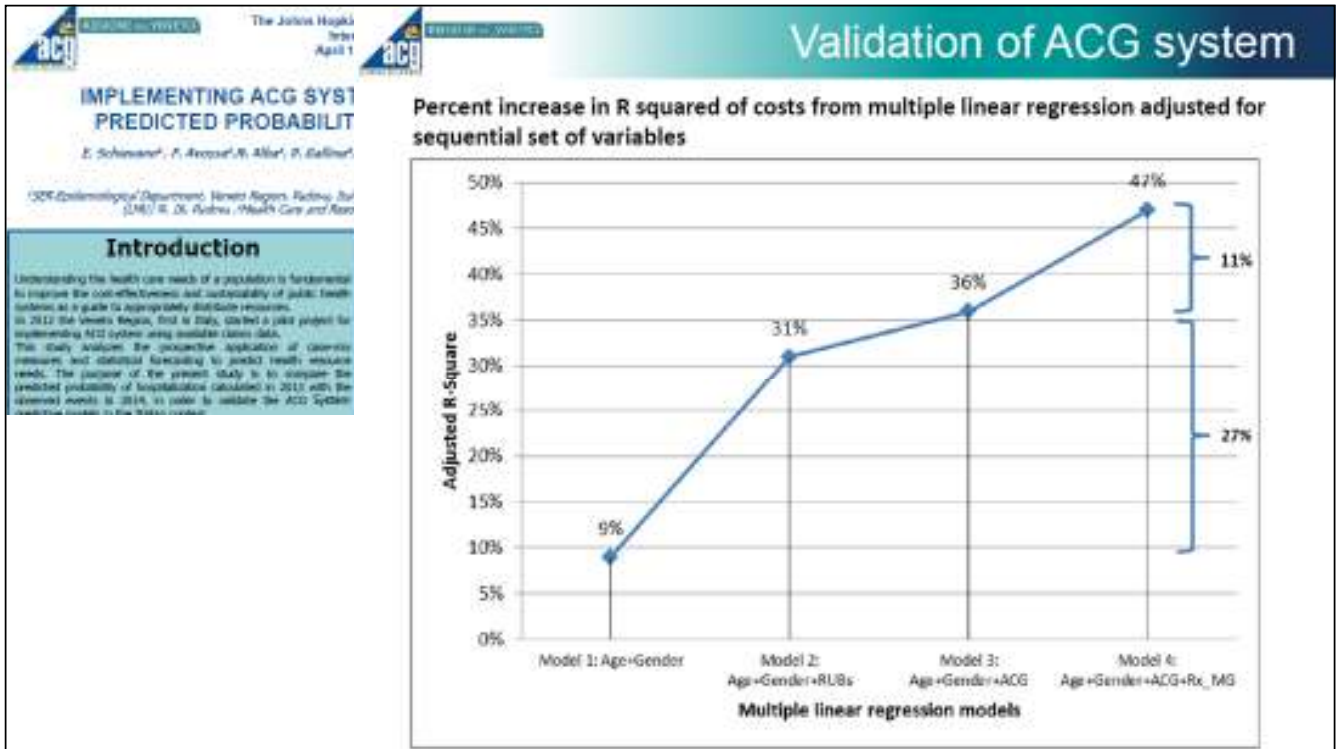
POPULATION
HEALTH ANALYTICS

PREDICTIVE HOSPITALIZATION MODELS

Predictive Model	Positive Predictive Value	Sensitivity
IP Hospitalization with prior cost and diagnosis and pharmacy data input	33.3%	21.2%
IP Hospitalization with prior cost and diagnosis data input	32.6%	20.8%
Prior cost only ¹¹	22.4%	14.2%

Predictive Model	Persons with Prior Hospitalization	Persons Aged less than 55 without Prior Hospitalization	Persons Aged 55 or older without Prior Hospitalization
IP Hospitalization	.751	.741	.718
IP Hospitalization Six Months	.754	.747	.728
ICU Hospitalization	.805	.757	.754
Injury Hospitalization	.808	.668	.748
Extended Hospitalization	.842	.721	.793

12



LINEAR MODELS UK '13 VS UK '16

Model	UK 2013 R ²	UK 2016 R ²
Total Cost	0.256	0.271
Drug Cost (based on total cost markers)	0.355	0.362
Drug Cost (based on pharmacy cost markers)		0.550

All statistics are based on validation model performance

Model	UK 2013 C-Stat	UK 2016 C-Stat
Total Cost 95th Percentile	0.845	0.873
Drug Cost 95th Percentile (total cost markers)	0.977	0.960
Drug Cost 95th Percentile (pharmacy cost markers)		0.978
Any Admission next 12 months	0.763	0.780
Any Admission next 6 months	0.782	0.801
Any Admission Length of Stay 12 days+	0.901	0.912
Unplanned (Emergency) Admission	0.773	0.786

All statistics are based on validation model performance

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.
<https://pubmed.ncbi.nlm.nih.gov/35420752/>

Gawande A. *The hot spotters*. The New Yorker. January 24, 2011:40-51
<https://www.newyorker.com/magazine/2011/01/24/the-hot-spotters>

Starfield et al, *Multimorbidity and its measurement*. Health Policy. 2011 Nov;103(1):3-8.
<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



JOHNS HOPKINS MEDICINE **POPULATION HEALTH ANALYTICS** **CONCLUSIONS**

- Comprehensive person-based records are key
- Local recalibration ensures models are relevant to the population
- Better overall performance than the original models
- New or additional local data variables and definitions
- Traditional modelling techniques (logistic and linear regression) models can be created efficiently, provide good face validity
- Casemix classifications reduce data complexity and provide robust measures of key constructs such as multimorbidity



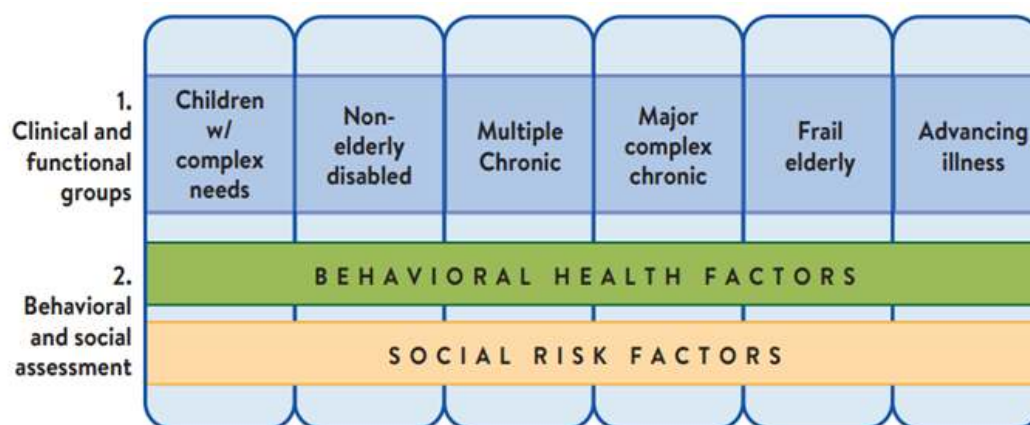
- Historically emphasis of work on identifying highest risk individuals
- Increased interest in recognising earlier and emerging risk, for proactive care management (+pandemic effects)
- Emerging data from Electronic Health Records (EHR), Personal Health Records (PHR), and Social Care data
 - Multi-level models, blended models
- Machine learning (AI?)
 - Efficiency, effectiveness, Synthetic data, interpretation, understanding, validation
- Bias in models, both direct and indirect a concern (+pandemic effect)
 - Applicability and validation across multiple segments

19

10

10/6/2022

Conceptual model of a starter taxonomy for high-need patients



Long P, Abrams M et al. Effective Care for High-Need Patients: Opportunities for Improving Outcomes, Value, and Health. National Academy of medicine fund. 2017. <https://nam.edu/HighNeeds/highNeedPatients.html>

20



- Starfield et al, Multimorbidity and its measurement. Health Policy. 2011 Nov;103(1):3-8.
<https://www.ncbi.nlm.nih.gov/pubmed/21963153>
- Forrest et al, Medication, diagnostic, and cost information as predictors of high-risk patients in need of care management. Am J Manag Care. 2009 Jan;15(1):41-8.
<https://www.ncbi.nlm.nih.gov/pubmed/19146363>
- Klaus W. Lemke, Jonathan P. Weiner, Jeanne M. Clark. Development and Validation of a Model for Predicting Inpatient Hospitalization. Med Care. 2012 Feb;50(2):131-9
<https://pubmed.ncbi.nlm.nih.gov/22002640/>
- Shannon M.E. Murphy, Heather K. Castro, and Martha Sylvia. Predictive Modeling in Practice: Improving the Participant Identification Process for Care Management Programs Using Condition-Specific Cut Points. August 2011, 14(4): 205-210.
<https://doi.org/10.1089/pop.2010.0005>
- Zachary Predmore, Elham Hatef, Jonathan P. Weiner. Integrating Social and Behavioral Determinants of Health into Population Health Analytics: A Conceptual Framework and Suggested Road Map. Population Health Management Vol. 22, No. 6 Dec 2019.
<https://www.liebertpub.com/doi/abs/10.1089/pop.2018.0151>



Any Questions?

Stephen Sutch, DrPH
ssutch1@jhu.edu

