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

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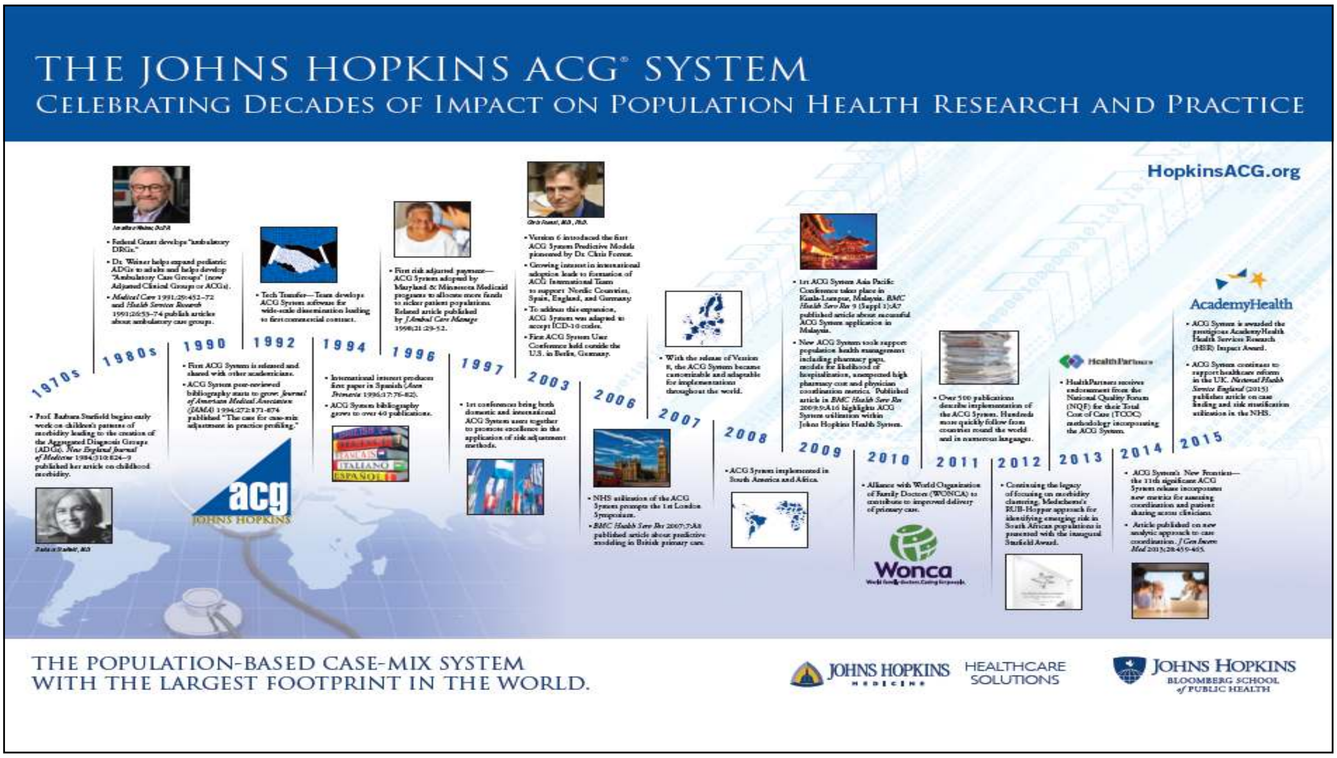

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PURPOSES OF PREDICTIVE MODELING

- 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)

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- 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

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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.

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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

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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

Results

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 Quintiles/IMS, One IMS 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

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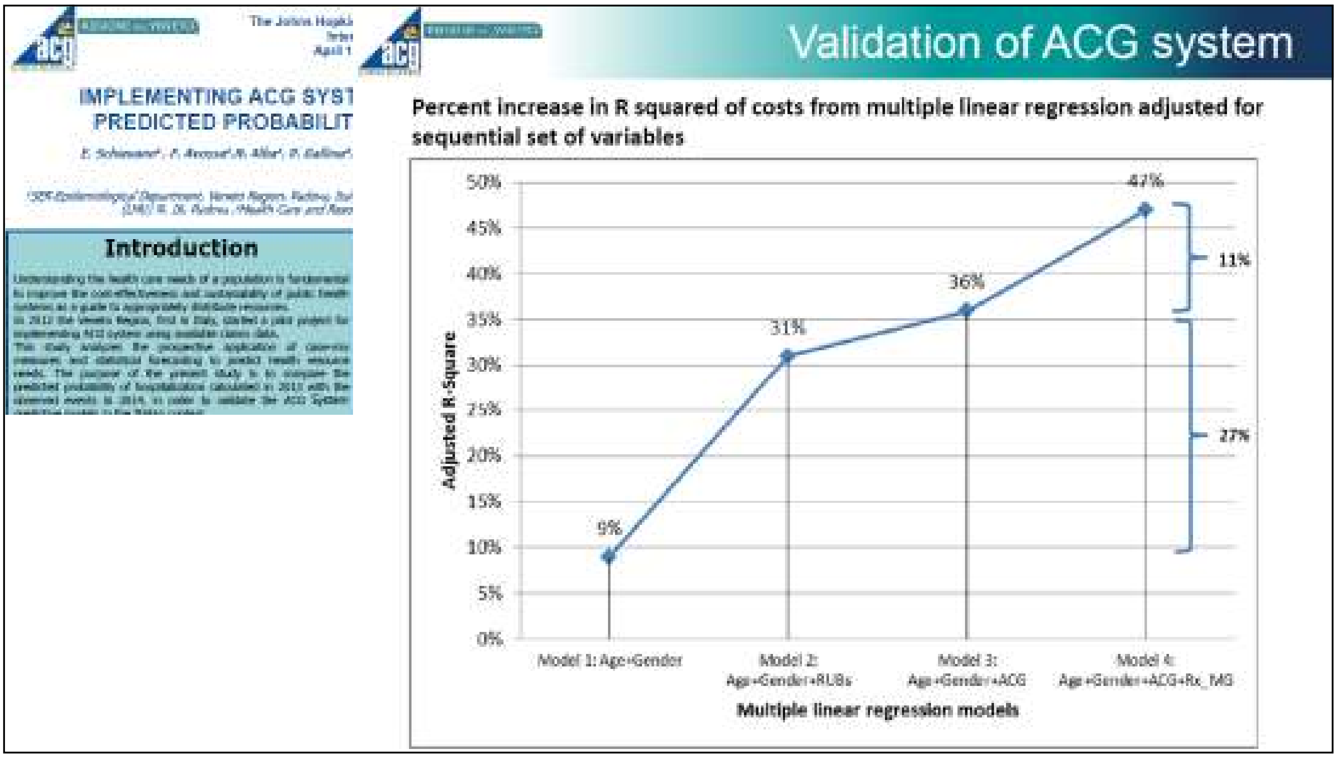
PREDICTIVE HOSPITALIZATION MODELS

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



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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

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BINARY MODELS UK '13 VS UK '16

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.
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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

Discussion

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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

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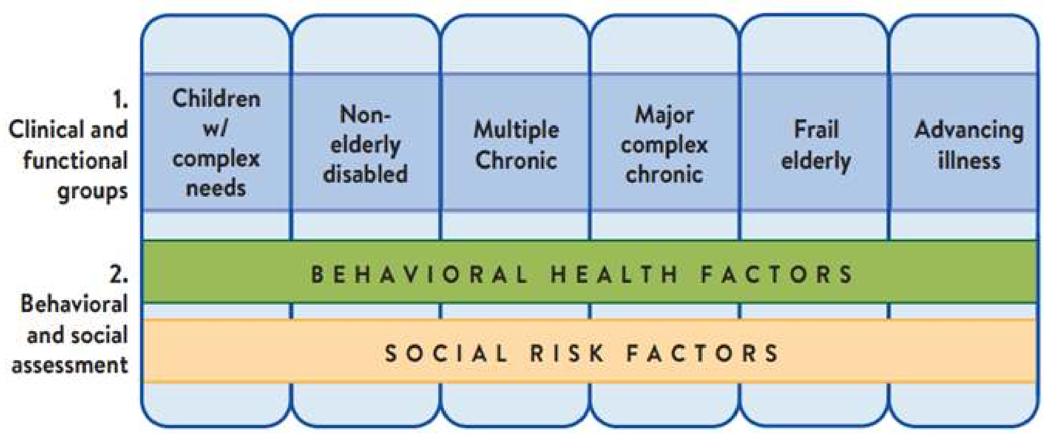
DISCUSSION

- 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

Conceptual model of a starter taxonomy for high-need patients



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Any Questions?

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