# How well do cardiovascular CPMs validate?

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# Outline

- A Clinical Example of Prediction
  External Validations
- External Validations
  - Heart failure
  - Review of the Literature
- Fully Independent External Validations
- OHDSI– Pooled Cohort Equation results

# **A Problem with Predictions**

There is no standard evaluation framework for CPMs and it is often merely assumed that predictions are trustworthy and accurate.

More importantly it is assumed that clinical decisions based on these predictions are superior to decisions made without these tools (i.e., lead to better outcomes).

# **Heart Failure**

- 6.2 million people in United States have HF
- >650,000 new cases of HF diagnosed annually
- 50% morality within 5 years of diagnosis
- Total cost of HF in United States > \$40 billion annually

# **Heart Failure**

Patient A	Patient B
6o years old	85 years old
SBP 110	SBP 140
HR 99	HR 84
O2 98%	O2 95%
Cr 1.4	Cr o.9
Troponin < 0.05	Troponin 1.7
BNP 500	BNP 1400

### **ACCF/AHA Practice Guideline**

### 2013 ACCF/AHA Guideline for the Management of Heart Failure

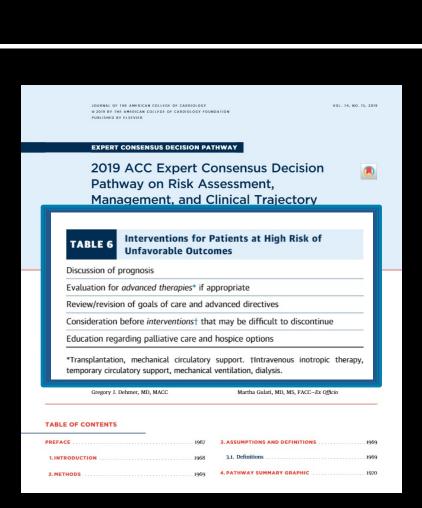
A Report of the American College of Cardiology Foundation/American Heart Association Task Force on Practice Guidelines

6.1.2. Risk Scoring: Recommendation

Class IIa

1. Validated multivariable risk scores can be useful to estimate subsequent risk of mortality in ambulatory or hospitalized patients with HF.<sup>199-207</sup> (Level of Evidence: B)

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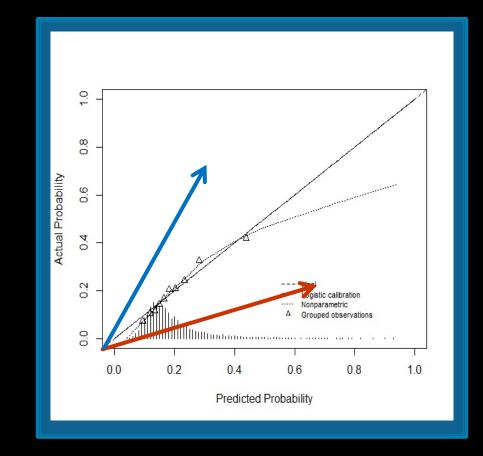
Yancy et al. Circulation 2013, Hollenberg et al. JACC 2019

## **CPM Performance: Discrimination**



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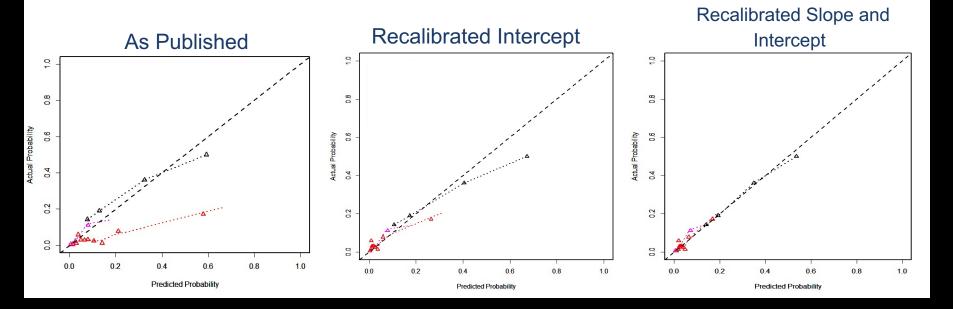
## **CPM Performance: Calibration**



## **External Validations: Discrimination**

СРМ	Derivation AUC	Worldwide AUC	N. America AUC	S. America	E. Europe AUC	W. Europe
GWTG-HF	0.75	0.64 (-44%)	0.70 (-20%)	0.52 (-92%)	0.65 (-40%)	0.65 (-40%)
OPTIME-CHF	0.77	0.72 (-19%)	0.69 (-30%)	0.71 (-22%)	0.71 (-22%)	0.66 (-41%)
EFFECT	0.77	0.66 (-41%)	0.72 (-19%)	0.58 (-70%)	0.62 (-56%)	0.69 (-30%)

## **External Validations: Calibration**



Model	Model Timeframe		South America	Eastern Europe	Western Europe				
woder	Ilmeirame	(Intercept, Slope)							
GWTG-HF	In hospital	1.21, 1.335	-2.783, 0.099	-0.318, 0.917	0.748, 1.061				
OPTIME-CHF	60 days	-1.777, 0.468	-1.482, 0.558	-1.849, 0.626	-1.983, 0.375				
EFFECT	1 year	0.070 <i>,</i> 0.965	-0.190, 0.461	-0.118, 0.687	-0.025, 0.854				

Wessler et al. JAHA 2017

# **Tufts PACE CPM Registry**



CONTACT US Tufts Medical

About CPM Registry Data Visualization Publications Resources

#### WELCOME TO THE TUFTS PACE CPM REGISTRY

The Predictive Analytics and Comparative Effectiveness (PACE) Center—led by David M. Kent, MD, MS at the Institute for Clinical Research and Health Policy Studies (ICRHPS) of Tufts Medical Center—presents the

#### **Clinical Prediction Model (CPM) Registry**

to help researchers and clinicians better understand the extent of cardiovascular and cerebrovascular disease CPM development and validation.









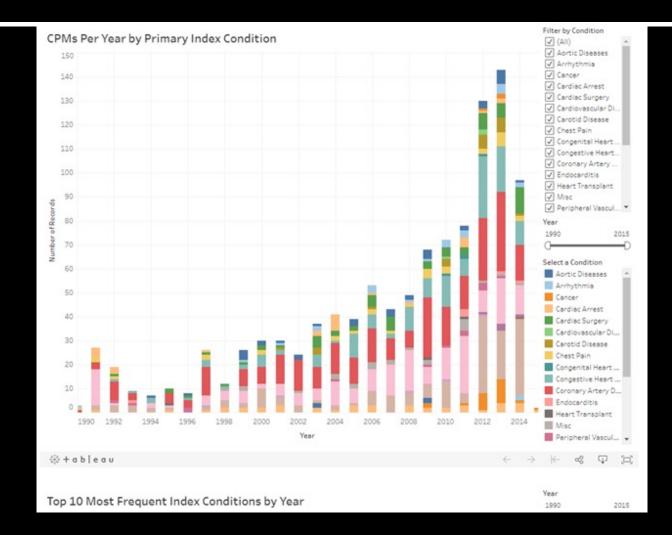
#### Featured Publications go to publications >>

News

- Clinical Prediction Models for Valvular Heart Disease Wessler BS, Lundquist CM, Koethe B, Park JG, Brown K, Williamson T, Ajlan M, Natto Z, Lutz JS, Paulus JK, Kent DM.
- A CPM Registry update is currently underway! A validation database has been added to the Registry, and Clinical prediction models published before

### Wessler et al. Circ COO 2015

# **Tufts PACE CPM Registry**



1382 clinical predictive models (CPMs)
 63% of de novo CPMs report a c-statistic

 We identified 2030 external validations of these CPMs

Wessler et al, CQO, in press

- Only 575 (42%) of the CPMs in the Registry have ever been externally validated.
- On average there were 1.5 validations per de novo CPM
- There was a very skewed distribution
  - The Logistic EuroSCORE has been validated 94 times

Top 10 Most Validated CPMs							
Model Name	Index Condition	Number of	Median validation	Range in validation			
	muex condition	validations	AUC (IQR)	AUC			
Logistic EuroSCORE	Cardiac Surgery	94	0.75 (0.67, 0.80)	0.48-0.90			
Additive EuroSCORE	Cardiac Surgery	86	0.77 (0.72, 0.82)	0.58-0.90			
EuroSCORE II	Valve Disease	65	0.76 (0.68, 0.81)	0.40-0.87			
GRACE	CAD: ACS	53	0.80 (0.73, 0.84)	0.60-0.95			
STS (valve) - Mortality	Cardiac Surgery	51	0.70 (0.64, 0.76)	0.45-0.85			
CHA <sub>2</sub> DS <sub>2</sub> -VASc	Arrhythmia	45	0.66 (0.61, 0.69)	0.45-0.93			
CHADS <sub>2</sub>	Arrhythmia	37	0.65 (0.61, 0.68)	0.51-0.87			
FRS - CHD	Population Sample	35	0.68 (0.63, 0.72)	0.54-0.80			
ICH Score	Stroke	27	0.85 (0.75, 0.87)	0.69-0.94			
ACEF Score	Cardiac Surgery	26	0.74 (0.68, 0.77)	0.54-0.87			

### Performance heterogeneity is the rule...

Wessler et al, CQO, in press

53% (n = 983) of the validations report some measure of CPM calibration.

 The Hosmer-Lemeshow test of goodness-of-fit was most commonly reported (30%), calibration-in-thelarge (26%), and calibration plots (22%).

There is no external assessment of calibration for 86% (n = 1182) of Cardiovascular Predictive Models

# **Conclusions from Prelim Work**

The tremendous proliferation and redundancy of CPMs is occurring without adequate—or even minimal—external evaluation.

Approximately 60% of published CPMs have never been externally validated. Approximately half of the CPMs that have been validated have been validated only once.

The value of single validations is unclear, since there is substantial performance heterogeneity and good (or poor) performance on a single validation does not appear to reliably forecast performance on subsequent validations.

# **Conclusions from Prelim Work**

This work raises substantial concerns about the current approach to 'validating' cardiovascular CPMs.

There should be a major rethinking of how performance heterogeneity is explored and quantified and how cardiovascular CPMs are evaluated for clinical use.

# Limitations of prelim work

- A major limitation of our literature review is that model performance is not generally presented in a way that makes it clear whether a given CPM is likely to improve or worsen decision making.
- Our main metric for model performance on external validation was the decrement in discrimination.
- The clinical significance of "change in discrimination" is unclear.

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- Fully Independent External Validations
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 We performed independent validations on a set of CPMs across 3 index conditions (acute coronary syndrome [ACS], heart failure [HF], and incident cardiovascular disease [CVD]) using publicly available clinical trial data and an evaluation framework.

# Independent validations: including novel measures

- Model Based c-statistic
  - Standardizes for case mix
- Measures of calibration:
  - Harrell's E<sub>avg</sub> and E<sub>90</sub> (standardized)
- Measures of clinical utility:
  - Decision curve analysis

# **Use of Decision Curves**

- Performance measures generally assess the quality of the predictions, not the quality of the decisions.
- ROC treats sensitivity and specific as equally important.

# But false negatives are generally worse than a false positive

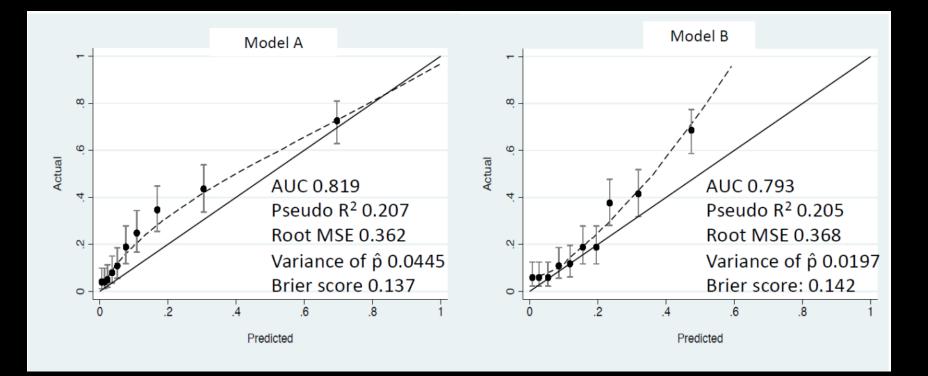


## **Decision curve analysis**

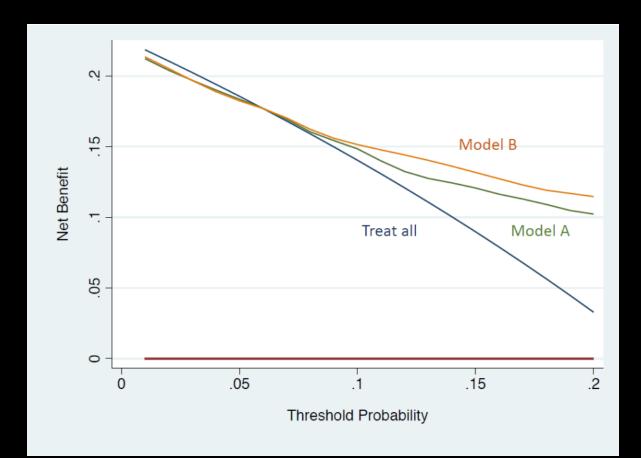
1. Select a  $p_t$ 2. Positive test defined as  $\hat{p} \ge p_t$ 3. Calculate "Clinical Net Benefit" as:  $\frac{TruePositiveCount}{n} - \frac{FalsePositiveCount}{n} \left(\frac{p_t}{1-p_t}\right)$ 

4. Vary  $p_t$  over an appropriate range

# Scenario 1: Select patients for biopsy amongst men with elevated PSA



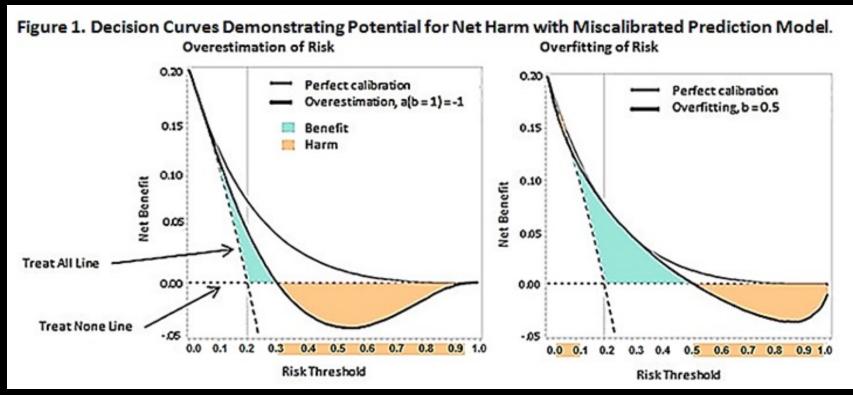
# Scenario 1: Select patients for biopsy amongst men with elevated PSA



## Decision curves do not help you pick the best decision threshold



## **Decision Curve: useful for detecting harm**



Schematic showing how miscalibration leads to harm, and recalibration protects against harm.

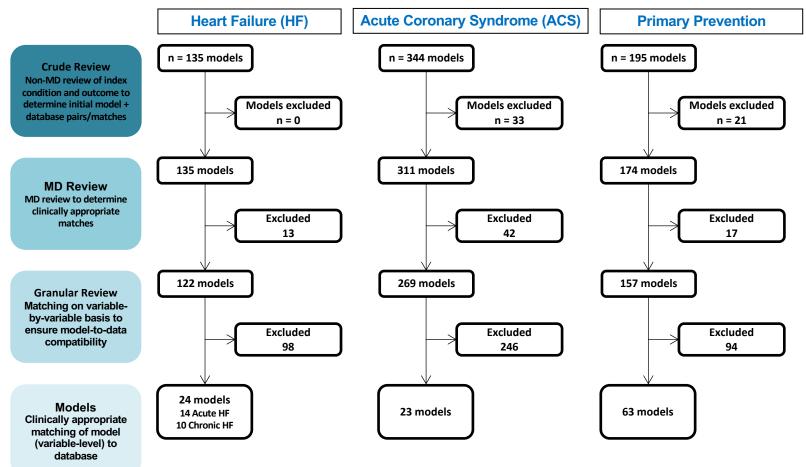
 We performed independent validations on a set of CPMs across 3 index conditions (acute coronary syndrome [ACS], heart failure [HF], and incident cardiovascular disease [CVD]) using publicly available clinical trial data and an evaluation framework.

# **36** Clinical Trials

Acute Coronary Syndrome AMIS ENRICHD MAGIC TIMI-II TIMI-III Heart Failure BEST DIG EVEREST TOPCAT HEAAL HF-ACTION SCD-HeFT SOLVD Population Sample ACCORD ALLHAT-HTN ALLHAT-LLT WHI

## 108 unique CPM tested 158 times

**Models overview** 



## Validation Performance All Matches



(n = 158)	Mean (SD)	Median (IQR)	Range				
Discrimination							
Development c-statistic	0.76 (0.05)	0.76 (0.73, 0.78)	0.63, 0.9				
Validation model-based c-statistic (MBc)	0.68 (0.06)	0.68 (0.66, 0.71)	0.52, 0.84				
Validation c-statistic	0.64 (0.06)	0.64 (0.6, 0.67)	0.44, 0.79				
% Change in discrimination due to							
Total (val.c vs. dev.c)	-46 (28)	-49 (-64, -29)	-138, 50				
Case mix heterogeneity (MBc vs. dev.c)	-27 (22)	-28 (-39, -13)	-88, 55				
Model validity (val.c vs. MBc)	-20 (60)	-24 (-43, -3)	-400, 400				
Calibration (12.4% observed outcome rat	te)						
Slope	0.69 (0.33)	0.64 (0.48, 0.84)	0.17, 2.5				
standardized E	0.9 (1.7)	0.5 (0.4, 0.7)	0, 14.2				
standardized E90	1.5 (2.3)	1 (0.6, 1.3)	0, 14.6				

\*26 distantly related validations (population CPMs) are not assessed for calibration

# **Validation Performance**



### Net Benefit Above Default Strategy (All Matches)

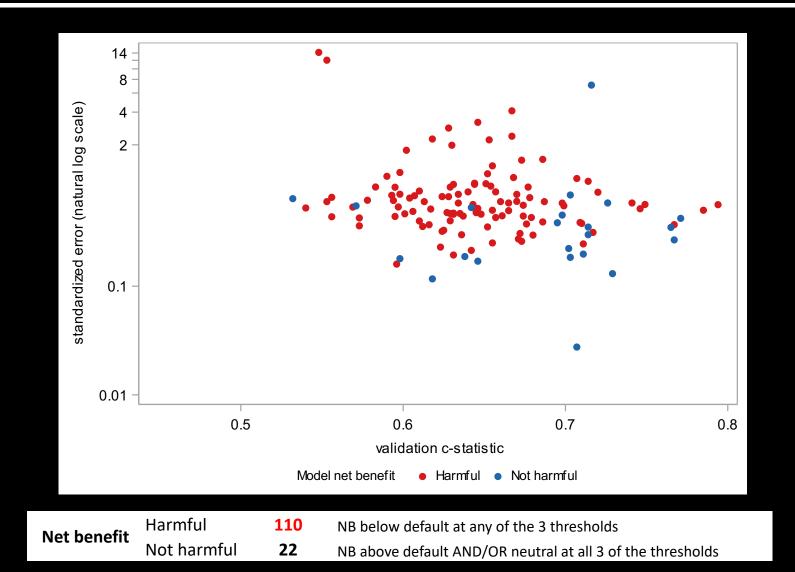
Validation	Threshold	N	Compared to default strategy			
Validation	Inresnoid	IN	% Above	% Neutral*	% Below	
	Prev./2	132	28.8	16.7	54.5	
Original model	Prevalence	132	85.6	6.8	7.6	
	Prev.*2	132	26.5	29.5	43.9	
	Prev./2	132	39.4	12.1	48.5	
Updated intercept	Prevalence	132	100.0	0.0	0.0	
	Prev.*2	132	49.2	10.6	40.2	
	Prev./2	132	52.3	28.8	18.9	
Updated intercept	Prevalence	132	100.0	0.0	0.0	
and slope	Prev.*2	132	56.1	24.2	19.7	
Re-estimated	Prev./2	132	68.2	14.4	17.4	
	Prevalence	132	100.0	0.0	0.0	
	Prev.*2	132	75.8	2.3	22.0	

\*Neutral defined as model NB equal to default strategy

# **Validation Performance**



Harmful vs Not harmful (original model)

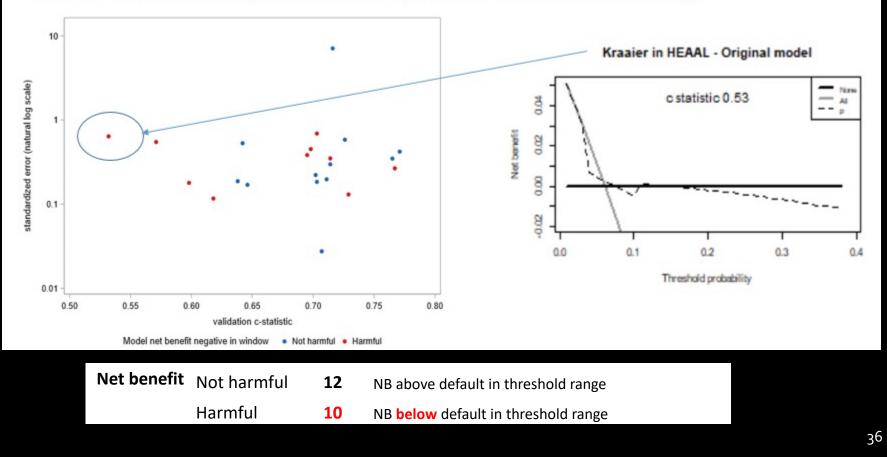


# **Validation Performance**

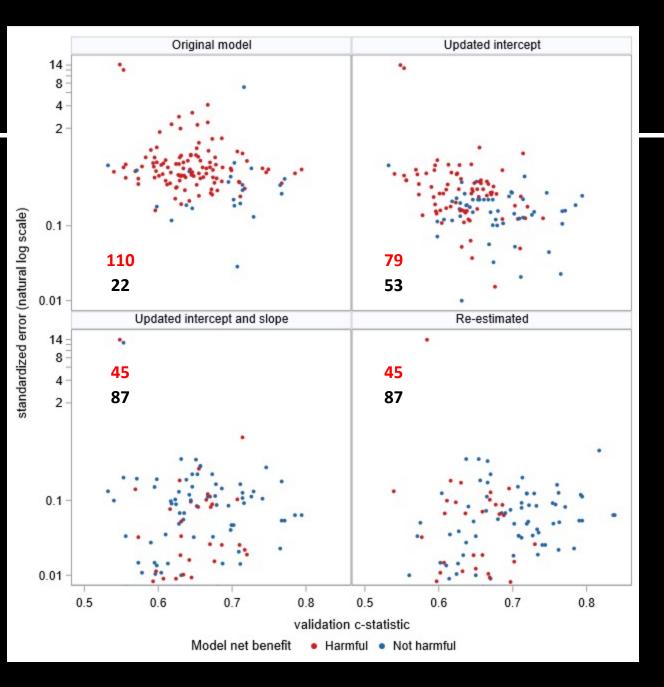
Harmful vs Not harmful (original model)

### N=22 defined as "not harmful" (blue dots from previous figure)

"harmful" = any NB in the range from half to twice prevalence that is below default strategy



**PACE** 



## IN PACE

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# The Clinical Focus of PROTEUS

- Cholesterol is a major modifiable risk factor for experiencing MI or stroke.
- Statins are widely available to decrease cholesterol levels and reduce rates of MI and stroke
- Individual predicted risk of MI or stroke is used to inform treatment with statins

### **ACC/AHA Prevention Guideline**

OPEN

### 2013 ACC/AHA Guideline on the Assessment of Cardiovascular Risk

#### A Report of the American College of Cardiology/American Heart Association Task Force on Practice Guidelines

Endorsed by the American Association of Cardiovascular and Pulmonary Rehabilitation, American Society for Preventive Cardiology, American Society of Hypertension, Association of Black Cardiologists, National Lipid Association, Preventive Cardiovascular Nurses Association, and WomenHeart: The National Coalition for Women With Heart Disease

#### EXPERT WORK GROUP MEMBERS

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Adults 40-75 years of age...with an estimated 10year ASCVD risk  $\ge 7.5\%$  should be treated with moderate- to high-intensity statin therapy.

10:57			
	≜ tools.acc.or	g — Private	
Estimate Risk	Ø Thera	py Impact	Ø Advice
	•••	•	
Value must be between	60-130		
Total Cholester	01 (mg/dL) *		
Value must be between	130 - 320		
HDL Cholestero	l (mg/dL) 🍍		
Value must be between	20 - 100		
LDL Cholesterol	(mg/dL) 🚯 <sup>O</sup>		
Value must be between	30-300		
History of Diabe	etes? *		
Yes			
Smoker? 🔁 *			
	Curren	t 🕄	
	Forme	r 🛈	
		<b>i</b>	
On Hypertensio	n Treatmer	nt? *	
Yes			

ACC/AHA Guideline on The Treatment of Blood Cholesterol

# **OHDSI Databases**

### Asia

- Ajou University School of Medicine Database (AUSOM)
- Japan Medical Data Center (JMDC)
- Europe
  - Clinical Practice Research Datalink (CPRD)
  - Integrated Primary Care Information (IPCI)
- US
  - Columbia University Irving Medical Center Data Warehouse (CUIMC)
  - IBM MarketScan<sup>®</sup> Commercial Database (CCAE)
  - Optum<sup>®</sup> De-identified Clinformatic Data Mart Database Date of Death (Optum DOD)
  - Optum<sup>®</sup> De-identified Electronic Health Record Dataset (Optum EHR)
  - The Stanford Medicine Research Data Repository (STARR-OMOP)
  - Tufts Research Data Warehouse (TRDW)

## **OHDSI** Databases

	Treated:	Untreated:					Total		
<b>.</b>	Systolic BP,	Systolic BP,	Age	Smoking	HDL-C, mg/dL	Male	Cholesterol,		
Database	mmHg	mmHg	(mean [SD])	(%)	(mean [SD])	(%)	mg/dL		
	(mean [SD])	(mean [SD])					(mean [SD])		
AUSOM	134.6 (21)	125.5 (15.3)	50.2 (9.5)	0	53.6 (13.3)	55.8	192.7 (33.1)		
CPRD	143.9 (19.6)	134.6 (18.7)	55.2 (10.3)	93.1	56.3 (14.3)	46.1	214.5 (37.1)		
CCAE	125.8 (12.9)	118.9 (12.4)	50 (6.9)	20.1	57.2 (14.8)	42	194 (31.7)		
СИМС	132.8 (18.3)	121.8 (15.4)	54.6 (10.7)	8.2	55.4 (14.9)	34.6	216.5 (35.7)		
IPCI	146.3 (20.1)	137.5 (19.4)	57.1 (9.9)	4.4	55.6 (13.5)	44.1	216.5 (35.7)		
JMDC	131.5 (15.7)	118.5 (15.3)	48.7 (7.5)	0.7	64.2 (14.6)	55.7	206.1 (32.3)		
Optum DOD	129 (15.2)	121.7 (14.3)	50.3 (8)	63.4	55.8 (14)	47.2	196.1 (32.8)		
Optum EHR	130.7 (16.5)	120.9 (13.9)	52.7 (10)	10.9	54.1 (14.6)	37.2	192.9 (31.4)		
STARR-OMOP	133.4 (18)	123.1 (15.3)	55.1 (10.6)	13.9	56.2 (14.8)	39.8	195.1 (33.8)		
TRDW	134.1 (18.3)	121.7 (14.5)	51.1 (9.9)	12.1	49.9 (13.9)	43.5	198.4 (34.5)		
BP indicates blood pressure; SD, standard deviation.									

BP indicates blood pressure, SD, standard deviation.

### Validation Results: Non-Black, Non-Female

Database	Outcomes	Ν	AUC	DAUC	Observed 3- year event rate (%)	standardized E (E <sub>avg</sub> /event rate)	standardized E90 (E <sub>90</sub> /event rate)	NB model @ threshold*
AUSOM	278	64997	0.816	-28.4	0.56	0.971	2.394	0.0003
CCAE	386	37321	0.668	31.9	1.47	0.249	0.307	0.0011
CPRD	9427	794858	0.732	5.9	1.44	1.544	2.78	-0.0013
CUIMC	179	9554	0.681	26.6	2.51	0.231	0.258	0.0063
IPCI	903	82028	0.67	31	1.49	1.012	2.626	-0.0002
JMDC	2232	390292	0.74	2.4	0.85	0.07	0.11	0.0008
		0	0					0
OPTUMDOD	22	7248	0.789	-17.4	2.72	0.135	0.177	0.0158
	<u> </u>		o =0 =		- 0-	a a 9a	a a 9a	
OPTUMEHR	688	49606	0.785	-15.9	1.85	0.082	0.083	0.007
STARR-OMOP	670	( ( 527	0.7/0	1 2	1.06	0.067	0.20/	0.0065
	670	44537	0.749	-1.2	1.96	0.007	0.204	0.0065
TUFTS	188	10867	0.752	-2.5	2.18	0 222	0 (70	
10115	100	1000/	0.752	-2.5	2.10	0.232	0.479	

\*Net Benefit decision threshold 2.25% (3 year follow up)

# **Validation Results**

Database	Outcomes	Ν	AUC	DAUC	Observed 3- year event rate (%)	standardized E (E <sub>avg</sub> /event rate)	standardized E90 (E <sub>90</sub> /event rate)	NB model @ threshold*
AUSOM	278	64997	0.816	-28.4	0.56	0.971	2.394	+
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CPRD	9427	794858	0.732	5.9	1.44	1.544	2.78	-
CUIMC	179	9554	0.681	26.6	2.51	0.231	0.258	+
IPCI	903	82028	0.67	31	1.49	1.012	2.626	-
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			-					
OPTUMEHR	688	49606	0.785	-15.9	1.85	0.082	0.083	+
	C C				C.	ć		
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	00	0.6			0			
TUFTS	188	10867	0.752	-2.5	2.18	0.232	0.479	

\*Net Benefit decision threshold 2.25% (3 year follow up)

## A Note about Model Performance

- There are several potential reasons why model performance might decrease
  - Overfitting
  - Changes in case mix

# Conclusions

- All measures of performance are highly variable
- For databases where PCE was highly miscalibrated, model use to support decision making would lead to net harm
   Re-calibration guards against harm

# Acknowledgements

- 262 OHDSI Symposium participants
- Evan Minty
- Jenna Reps
- Andrew Williams
- Patrick Ryan
- Jason Nelson
- And many others...