

Systematic reviews of prognosis studies III

Meta-analytical approaches in systematic reviews of prognostic studies

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for the Cochrane Prognosis Methods Group

Conflict of interest

We have no actual or potential conflict of interest in relation to this presentation



Prediction

- Risk prediction = foreseeing / foretelling
... (probability) of something that is yet unknown
- Turn available information (predictors) into a statement about the probability:
 - ... diagnosis
 - ... prognosis



What is the big difference between diagnostic and prognostic 'prediction'?

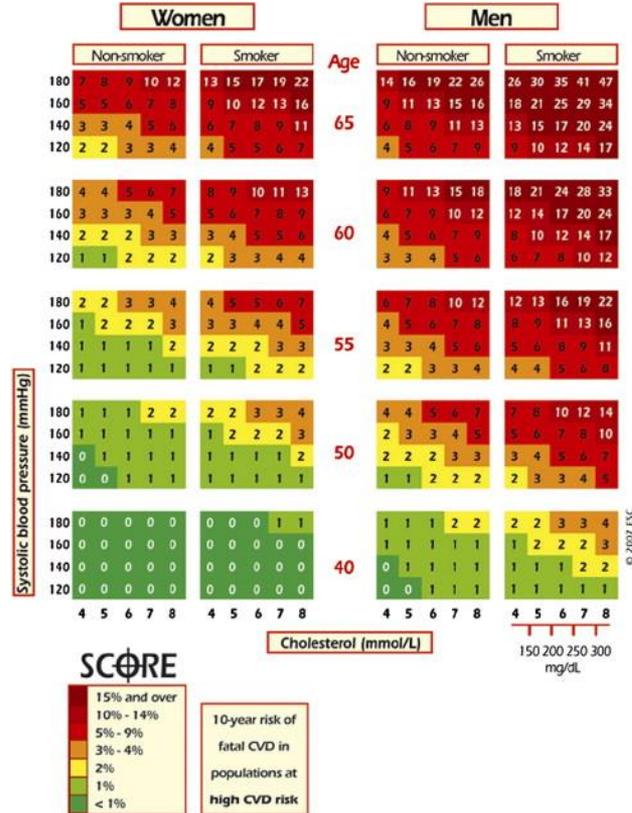


Prediction models

APGAR

Test Scoring

	Score 0	Score 1	Score 2
A ppearance			
	Blue all over	Blue only at extremities	No blue coloration
P ulse	No pulse	<100 beats/min.	>100 beats/min.
G rimace			
	No response to stimulation	Grimace or feeble cry when stimulated	Sneezing, coughing, or pulling away when stimulated
A ctivity			
	No movement	Some movement	Active movement
R espiration	No breathing	Weak, slow, or irregular breathing	Strong cry



Three phases of Prediction Modelling

1. Developing a prediction model
2. Validate (+update) the model in other subjects
3. Quantify model's impact on doctor's decision making and patient outcome (cost-effectiveness)

What is big difference between 3 versus 1-2?

Focus on 1-2

Two types of prediction modes: diagnostic and prognostic



Reviews of prognosis studies

Focus on MA of prognostic prediction models

Everything also applies to MA of diagnostic prediction models

Numerous prognostic models for same target population + outcomes

- >350 models for predicting cardiovascular disease
- >100 models for brain trauma patients
- >100 diabetes type 2 models
- > 60 models for breast cancer prognosis



Need for systematic reviews

Abundance of CPMs, with poor understanding of

- The comparative performance of these CPMs
- The consistency of accuracy and predictions across CPMs
- The clinical impact of these CPMs

Systematic review and MA validation studies of one or more certain models may help to identify promising models and evaluate the need for further improvements of these models.



Why do we need meta-analysis?

Quantitative synthesis (meta-analysis) may help

- To summarize the predictive performance of a certain CPM across multiple validation studies
- To evaluate whether a certain CPM yields consistently good performance across different populations, outcomes, etc.
- To establish boundaries of applicability and generalizability
- To identify possible improvements of CPMs



Is MA even possible?

You need multiple validation studies of same model!

Ex. Prognostic prediction models for cardiovascular disease

Top 5 validated models	N
Framingham (Wilson 1998)	80
Framingham (Anderson 1991 Am H J)	73
SCORE (Conroy 2003)	63
Framingham (D'Agostino 2008)	44
Framingham (no reference)	32



Is MA of prediction models even possible?

- Model validation studies are increasingly common!
E.g. Framingham, EuroSCORE, Gail, ...
- Reporting of model validation studies is steadily improving!
E.g. due to reporting guidelines (TRIPOD)

Annals of Internal Medicine RESEARCH AND REPORTING METHODS

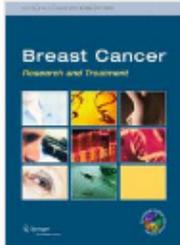
Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD): Explanation and Elaboration

Ann Intern Med. 2015;162:W1-W73. doi:10.7326/M14-0698

Karel G.M. Moons, PhD; Douglas G. Altman, DSc; Johannes B. Reitsma, MD, PhD; John P.A. Ioannidis, MD, DSc;
Petra Macaskill, PhD; Ewout W. Steyerberg, PhD; Andrew J. Vickers, PhD; David F. Ransohoff, MD; and Gary S. Collins, PhD



Is MA even possible?



[Breast Cancer Research and Treatment](#)

..... April 2012, Volume 132, [Issue 2](#), pp 365–377

A systematic review of breast cancer incidence risk prediction models with meta-analysis of their performance

Authors

[Authors and affiliations](#)

Catherine Meads , Ikhlmaq Ahmed, Richard D. Riley

Review

First Online: [22 October 2011](#)

DOI: [10.1007/s10549-011-1818-2](#)

Cite this article as:

Meads, C., Ahmed, I. & Riley, R.D.

Breast Cancer Res Treat (2012) 132:

365. doi:[10.1007/s10549-011-1818-2](#)

47

1.4k

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Is MA even possible?

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Predictive performance of the CHA2DS2-VASc rule in atrial fibrillation: a systematic review and meta-analysis

Sander van Doorn , Thomas P.A. Debray, Femke Kaasenbrood, Arno W. Hoes, Frans H. Rutten, Karel G.M. Moons, Geert-Jan Geersing

Accepted manuscript online: 4 April 2017 [Full publication history](#)

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Guidance papers

RESEARCH METHODS AND REPORTING



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A guide to systematic review and meta-analysis of prediction model performance

Thomas P A Debray,^{1,2} Johanna A A G Damen,^{1,2} Kym I E Snell,³ Joie Ensor,³ Lotty Hooft,^{1,2} Johannes B Reit

Article

A framework for meta-analysis of prediction model studies with binary and time-to-event outcomes

Thomas PA Debray,^{1,2}  Johanna AAG Damen,^{1,2} Richard D Riley,³ Kym Snell,³  Johannes B Reitsma,^{1,2} Lotty Hooft,^{1,2} Gary S Collins⁴  and Karel GM Moons^{1,2}

SMMR
STATISTICAL METHODS IN MEDICAL RESEARCH

Statistical Methods in Medical Research
0(0) 1–19

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journals.sagepub.com/home/smm

 SAGE

Required steps of the SR

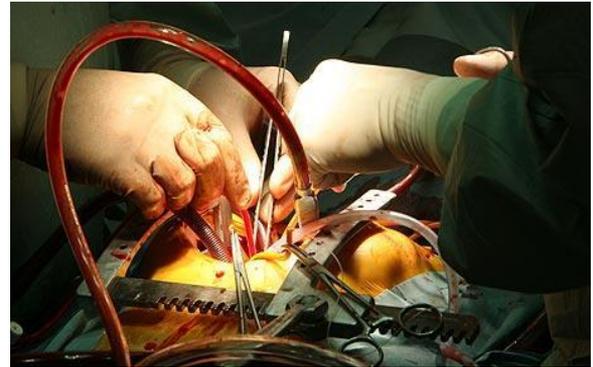
1. Formulating the review question
2. Formulating the search strategy
3. Critical appraisal (CHARMS & PROBAST)
4. Quantitative data extraction
5. Meta-analysis
6. Investigating heterogeneity across studies
7. Sensitivity analyses
8. Reporting



Illustrative example: EuroSCORE

Predicting 30 day mortality after cardiac surgery

- Cardiac surgery in high-risk population
- Need for risk stratification
- Establish risk profile of cardiac surgical patients using multivariable prediction models
- Establish prediction model performance



Illustrative example: EuroSCORE

Patient related factors			Cardiac related factors		
Age ¹ (years)	<input type="text" value="0"/>	<input type="text" value="0"/>	NYHA	<input type="text" value="select"/>	<input type="text" value="0"/>
Gender	<input type="text" value="select"/>	<input type="text" value="0"/>	CCS class 4 angina ⁸	<input type="text" value="no"/>	<input type="text" value="0"/>
Renal impairment ² <small>See calculator below for creatinine clearance</small>	<input type="text" value="normal (CC >85ml/min)"/>	<input type="text" value="0"/>	LV function	<input type="text" value="select"/>	<input type="text" value="0"/>
Extracardiac arteriopathy ³	<input type="text" value="no"/>	<input type="text" value="0"/>	Recent MI ⁹	<input type="text" value="no"/>	<input type="text" value="0"/>
Poor mobility ⁴	<input type="text" value="no"/>	<input type="text" value="0"/>	Pulmonary hypertension ¹⁰	<input type="text" value="no"/>	<input type="text" value="0"/>
Previous cardiac surgery	<input type="text" value="no"/>	<input type="text" value="0"/>	Operation related factors		
Chronic lung disease ⁵	<input type="text" value="no"/>	<input type="text" value="0"/>	Urgency ¹¹	<input type="text" value="elective"/>	<input type="text" value="0"/>
Active endocarditis ⁶	<input type="text" value="no"/>	<input type="text" value="0"/>	Weight of the intervention ¹²	<input type="text" value="isolated CABG"/>	<input type="text" value="0"/>
Critical preoperative state ⁷	<input type="text" value="no"/>	<input type="text" value="0"/>	Surgery on thoracic aorta	<input type="text" value="no"/>	<input type="text" value="0"/>
Diabetes on insulin	<input type="text" value="no"/>	<input type="text" value="0"/>			
EuroSCORE II <input type="text" value="EuroSCORE II"/>		<input type="text" value="0"/>			
 <small>Note: This is the 2011 EuroSCORE II</small>		<input type="button" value="Calculate"/> <input type="button" value="Clear"/>			

Step 1

Formulating the review question and protocol

Formulating the review question and protocol

- Describe rationale, objectives, design, methodology and statistical considerations of the systematic review
- Define the PICOTS

Extensively discussed in workshop 1!



Illustrative example: EuroSCORE

<u>P</u> opulation	Patients undergoing coronary artery bypass grafting
<u>I</u> ntervention	The (additive) EuroSCORE model
<u>C</u> omparator	Not applicable
<u>O</u> utcome(s)	All cause mortality
<u>T</u> iming	30 days, predicted using peri-operative conditions
<u>S</u> etting	risk stratification in the assessment of cardiac surgical results

Step 2

Formulating the search strategy

Formulating the search strategy

- Use information from the PICOTS
- Combine with existing search filters
- Evaluate citations of the development paper

Tools: electronic databases, conference abstracts, hand searching, online registers

Extensively discussed in workshop 1!



Step 3

Critical appraisal

Critical appraisal

Evaluate **bias and applicability** of each validation study

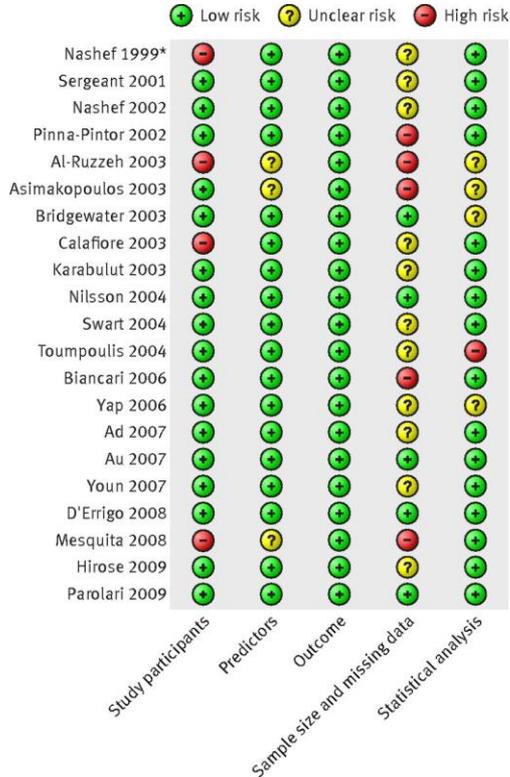
- CHARMS checklist
- PROBAST (2018)

Decide whether studies should be excluded due to low quality and/or applicability with respect to the current review

Extensively discussed in workshop 2!



Illustrative example: EuroSCORE



Overall judgment for risk of bias of included articles

(21 studies, involving 22 validations)



Step 4

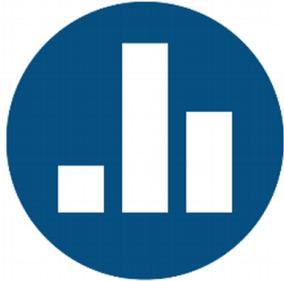
Quantitative data extraction and preparation

Recap: what are validation studies?

- Test a previously developed prediction model into new individuals
 - Same population
 - Different but related population
- Evaluate the predictive accuracy
 - Overall performance
 - Calibration
 - Discrimination



Recap: what are validation studies?



What statistics can we summarize when reviewing external validation studies?



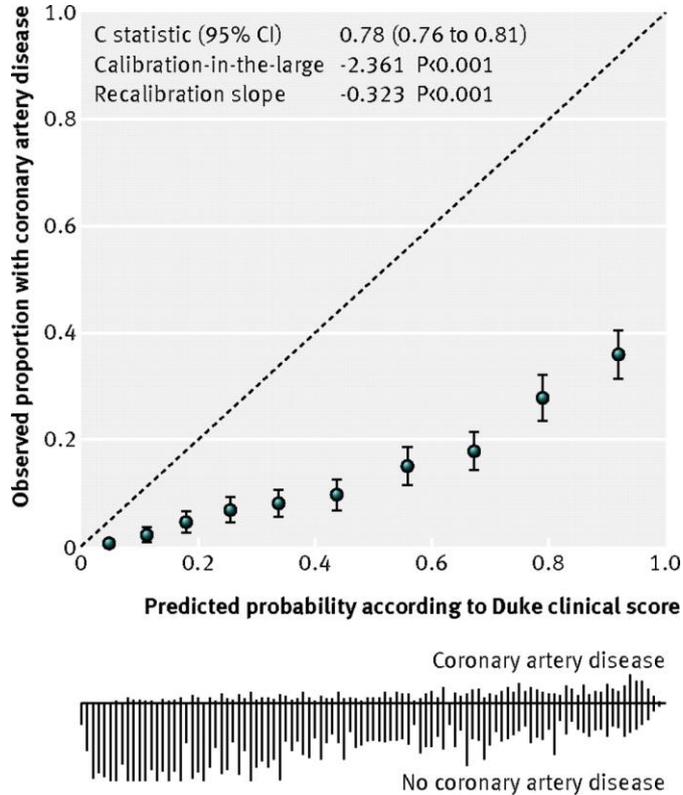
Discrimination

Quantifies the model's extent to distinguish between events and non-events

- Visual inspection
 - Receiving Operating Characteristics (ROC) curve
- Summary statistics
 - Concordance (c) index
 - Area under the ROC curve (AUC)
 - Discrimination slope



Calibration



Agreement between observed outcomes and predictions

- Total O:E ratio
- Calibration intercept
- Calibration slope



Calibration table – good model?

External validation of EuroSCORE

Expected mortality (%) versus observed in-hospital mortality

Score	N	Expected	Observed
0-2	201	1.4	0.5
3-5	309	4.0	1.0
6-8	181	6.8	2.2
>= 9	66	10.5	3.0



Quantitative data extraction and preparation

Common problems in data extraction

- Selective/inconsistent reporting
- Incomplete assessments (e.g. calibration)
- Missing estimates of precision (e.g. standard error)

Solutions

- C-statistic, O:E ratio and calibration slope can often be derived from reported information
- Several approximations have been proposed to obtain estimates for missing standard errors



Quantitative data extraction and preparation

metamisc: Diagnostic and Prognostic Meta-Analysis

Meta-analysis of diagnostic and prognostic modeling studies. Summarize estimates of prognostic factors, diagnostic test accuracy and prediction model performance. Validate, update and combine published prediction models. Develop new prediction models with data from multiple studies.

Version: 0.1.9
Depends: R ($\geq 3.2.0$), stats, graphics
Imports: [metafor](#) ($\geq 2.0.0$), [mvtnorm](#), [ellipse](#), [lme4](#), [plyr](#), [ggplot2](#)
Suggests: [runjags](#), [rjags](#), [testthat](#) ($\geq 1.0.2$)
Published: 2018-05-13
Author: Thomas Debray  [aut, cre], Valentijn de Jong [aut]
Maintainer: Thomas Debray <thomas.debray at gmail.com>
License: [GPL-3](#)
URL: <http://r-forge.r-project.org/projects/metamisc/>
NeedsCompilation: no
In views: [MetaAnalysis](#)
CRAN checks: [metamisc results](#)

Downloads:

Reference manual: [metamisc.pdf](#)
Package source: [metamisc_0.1.9.tar.gz](#)
Windows binaries: r-devel: [metamisc_0.1.9.zip](#), r-release: [metamisc_0.1.9.zip](#), r-oldrel: [metamisc_0.1.9.zip](#)
OS X binaries: r-release: [metamisc_0.1.9.tgz](#), r-oldrel: [metamisc_0.1.9.tgz](#)
Old sources: [metamisc archive](#)

Linking:

Please use the canonical form <https://CRAN.R-project.org/package=metamisc> to link to this page.



Quantitative data extraction and preparation

- Information on case-mix variation
 - Mean & standard deviation of key subject characteristics
 - Mean & standard deviation of the linear predictor
- Information on key study characteristics
 - Location
 - Standards w.r.t. treatments, patient referral, ...



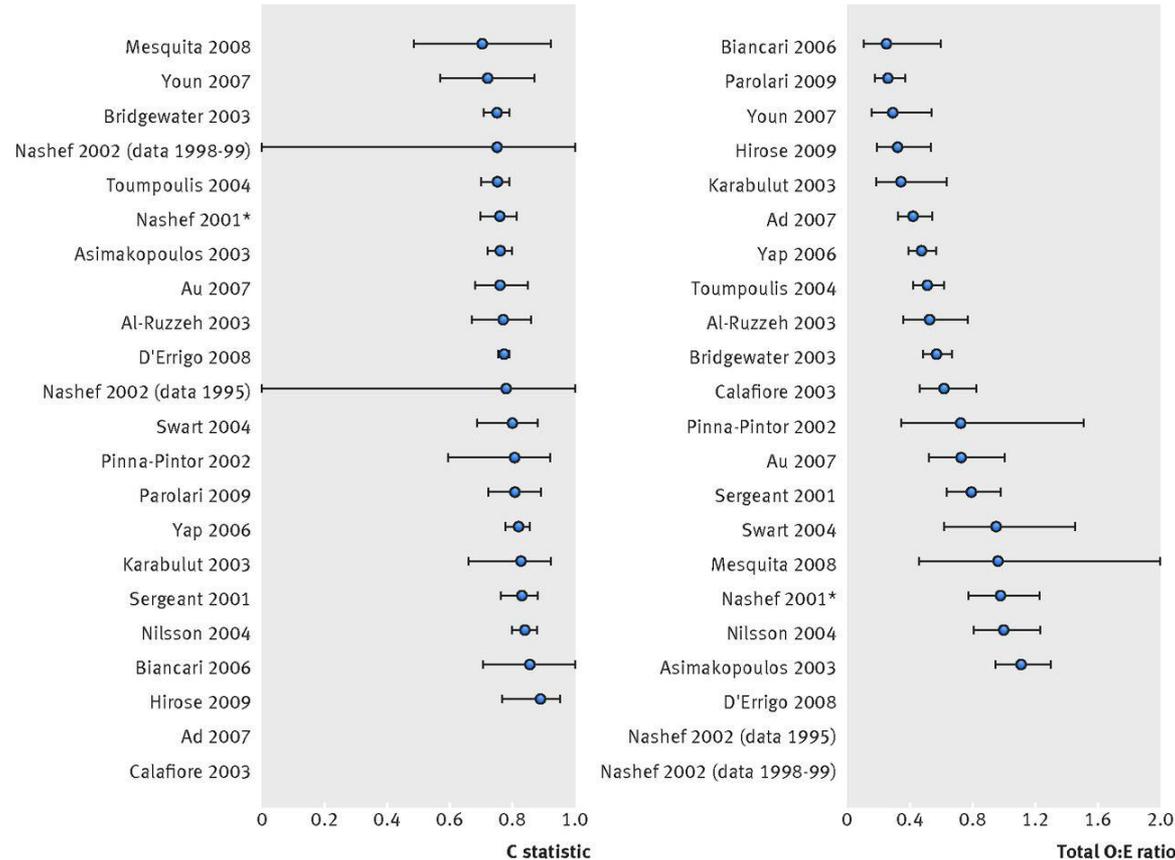
Illustrative example: EuroSCORE

Predictive performance of the EuroSCORE

- C-statistic
 - Summary statistic reported in 20 validations
 - SE approximated for 7 studies
- O:E
 - Relevant information obtained for 21 validations



Illustrative example: EuroSCORE



Step 5

Meta-analysis

Meta-analysis

Fixed or random effects?

- Fixed effect meta-analysis
 - The model's *true* predictive accuracy is the same for all validation studies
 - Variation in predictive accuracy only appears due to chance
- Random effects meta-analysis
 - The model's *true* predictive accuracy differs across validation studies
 - Variation in predictive accuracy arises from sampling error and between-study heterogeneity



Meta-analysis

Homogeneous model performance often unrealistic

- Validation studies typically differ in design, execution and case-mix variation
- Ignoring heterogeneity leads to an overly precise summary result
- Summary estimates of predictive accuracy have limited usefulness when there is strong heterogeneity



Meta-analysis

Traditional meta-analysis methods approximate within-study variability with a **Normal distribution**. This approximation may introduce bias or show other poor statistical properties when

- The c-statistic or O:E ratio is close to 0 or 1
- When sample sizes are relatively small

Need for transformations!

- Meta-analysis of **logit** c-statistic
- Meta-analysis of **log** O:E ratio



Meta-analysis

Quantifying heterogeneity

Prediction interval

- Combines the standard error of the summary estimate with the estimate for between-study variability
- Typically based on Student's t distribution
- Provides a range for the potential predictive accuracy in a new validation study
- Ideally calculated from 10 or more validation studies



Meta-analysis

Quantifying heterogeneity

Probability of “good” performance

- Calculate the likelihood of achieving a certain c-statistic and/or total O:E ratio in a new validation study
- Rough indication of model generalizability



Illustrative example: EuroSCORE

Meta-analysis	N	Summary	95% CI	95% PI
C-statistic	18	0.78	0.76 – 0.80	0.73 – 0.83
O:E ratio	19	0.55	0.43 – 0.69	0.20 – 1.53

- Probability of “good” discrimination ($c > 0.75$) = **89%**
- Probability of “good” calibration ($0.8 \leq O:E \leq 1.2$) = **15%**



Step 6

Investigating heterogeneity across studies

Investigating heterogeneity across studies

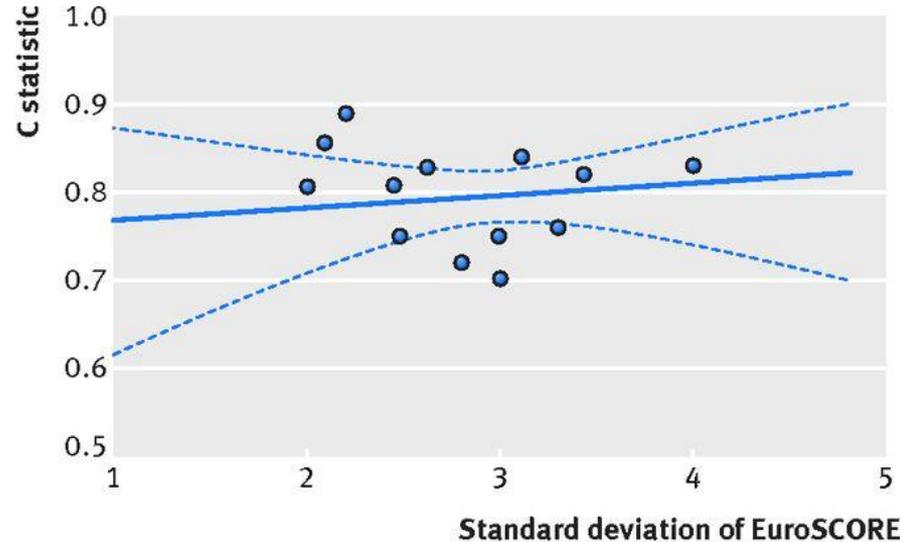
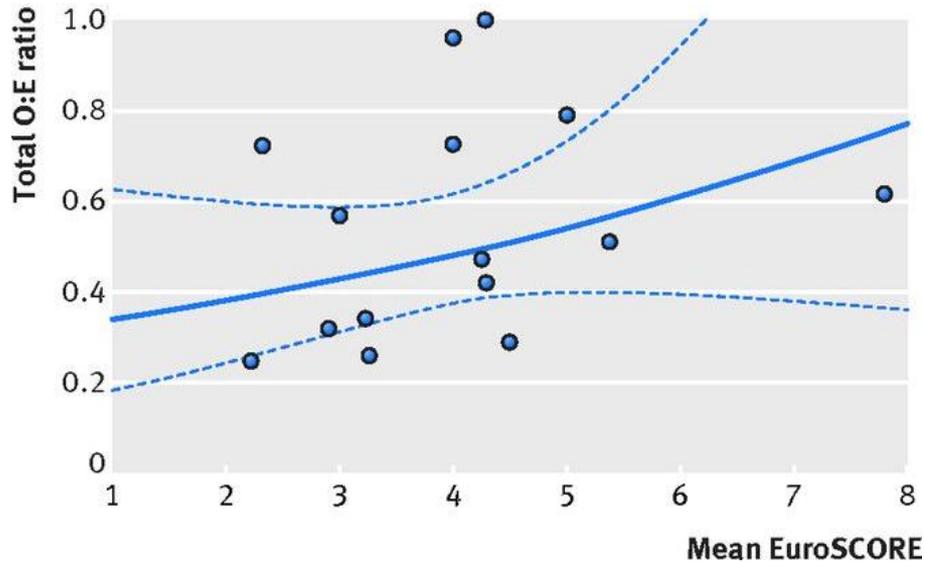
Meta-regression to adjust the meta-analysis for study-level variables

- Study characteristics
 - *Study design, follow-up, ...*
 - *Predictor- and outcome definitions*
- Population characteristics
 - *Distribution of linear predictor or individual covariates*
 - *Treatment standards (**beware of ecological fallacy**)*



Illustrative example: EuroSCORE

Adjustment for case-mix variation



Step 7

Sensitivity analyses

Sensitivity analyses

Evaluate the robustness of drawn conclusions

- Influence of low(er) quality validation studies
- Influence of key modelling assumptions
 - Use of “exact” likelihood models
 - Joint pooling of discrimination and calibration
- ...



Illustrative example: EuroSCORE

Meta-analysis	ROB	M	Summary	95% CI	95% PI
C-statistic	All	18	0.78	0.76 – 0.80	0.73 – 0.83
	Low	4	0.80	0.73 – 0.85	0.66 – 0.89
O:E ratio	All	19	0.55	0.43 – 0.69	0.20 – 1.53
	Low	3	0.57	0.10 – 3.33	0.02 – 19.15



Step 8

Reporting

Reporting

Relevant guidelines

- PRISMA
- TRIPOD
- GRADE



Case study

Performance of the Pooled Cohort Equations prognostic model

Step 1

Formulating the review question and protocol

Predictive performance of PCE

<u>P</u> opulation	General population
<u>I</u> ntervention	PCE
<u>C</u> omparator	Framingham Wilson and ATP III
<u>O</u> utcome(s)	Cardiovascular Disease (CVD)
<u>T</u> iming	10 year
<u>S</u> etting	Primary care and public health

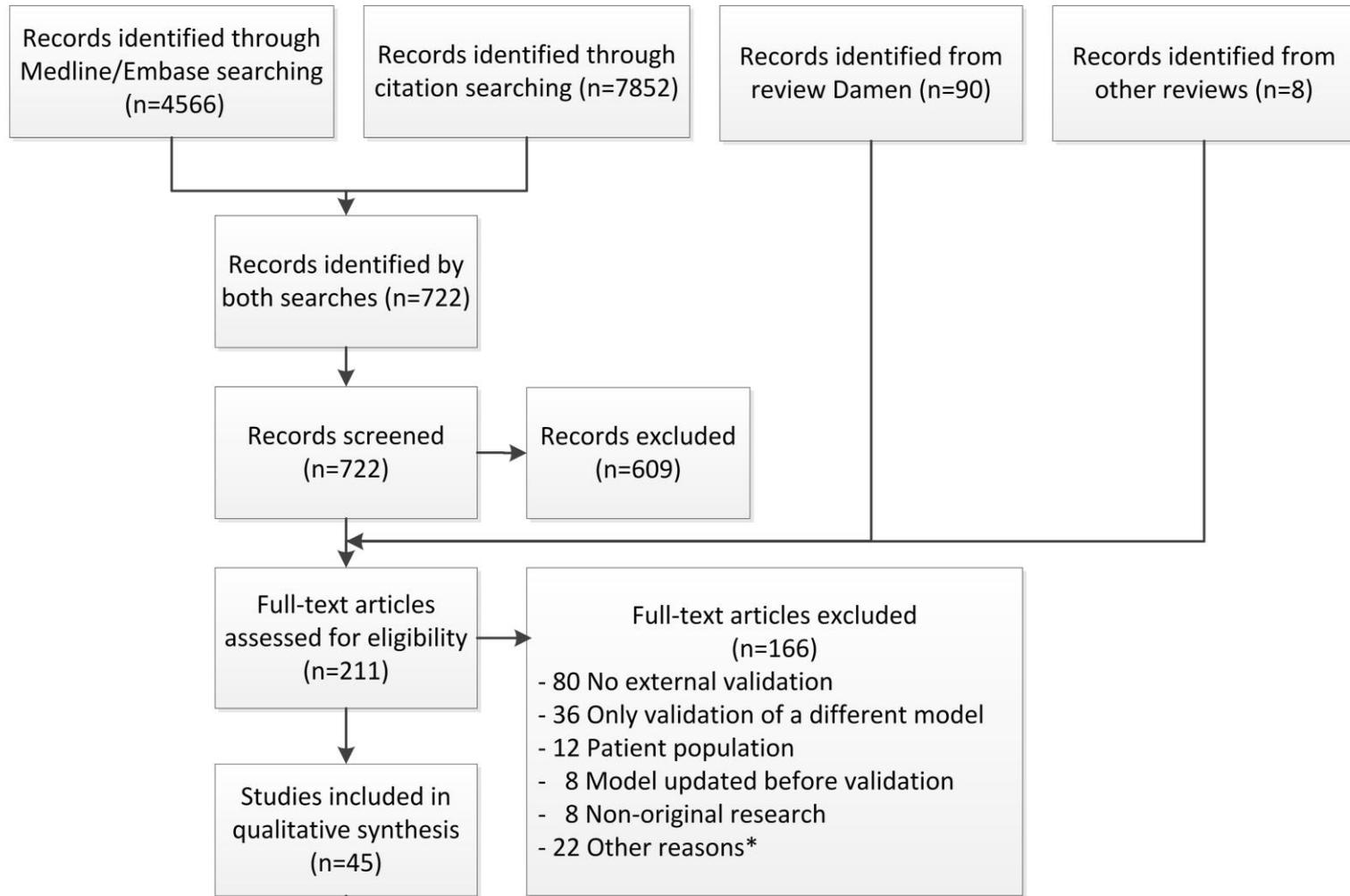
Step 2

Formulating the search strategy

- Articles published before June 2013 selected from a previous review¹
- Update using citation search

¹BMJ 2016;353:i2416

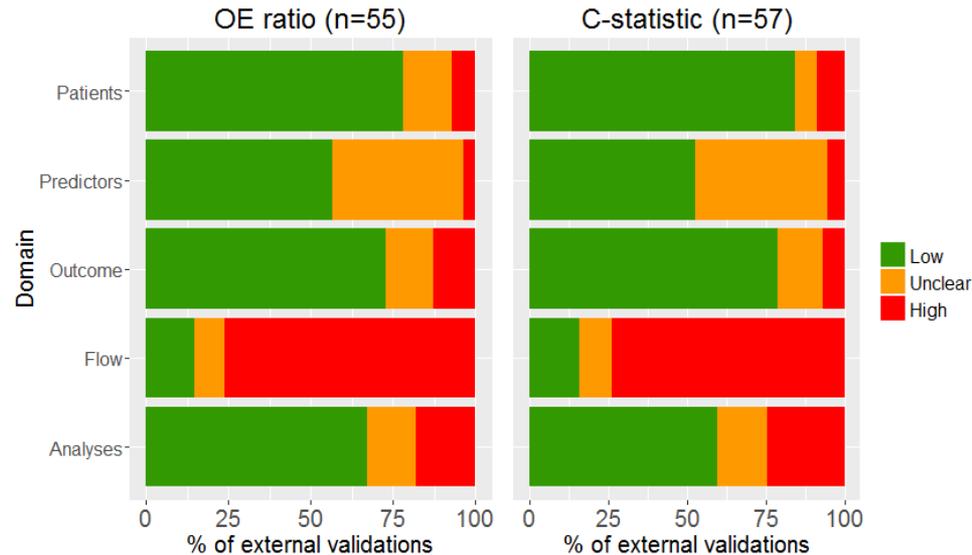




Step 3

Critical appraisal

Risk of bias assessed using a preliminary version of PROBAST



Step 4

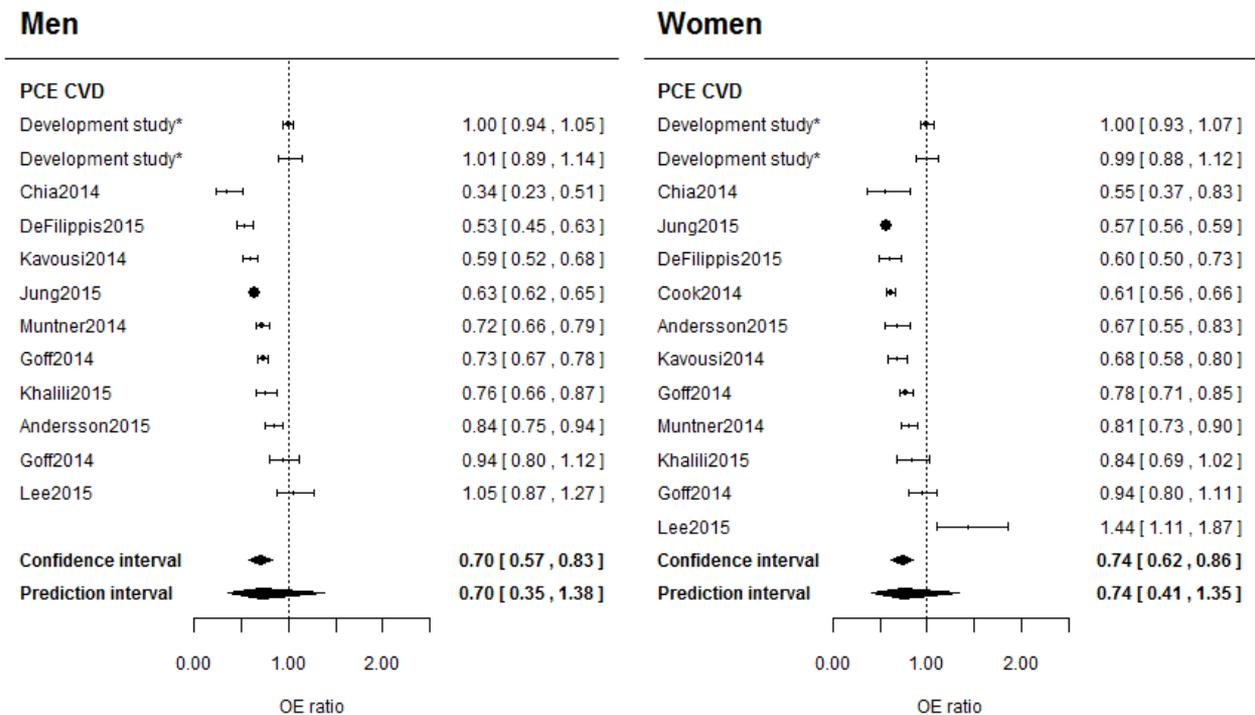
Quantitative data extraction and preparation

Items extracted	
Study design	Outcome definition
Study population, location	Sample size
Study dates	Model discrimination (c-statistic)
Case-mix	Model calibration (O:E ratio)
Predictors	Model calibration (slope)



Step 5

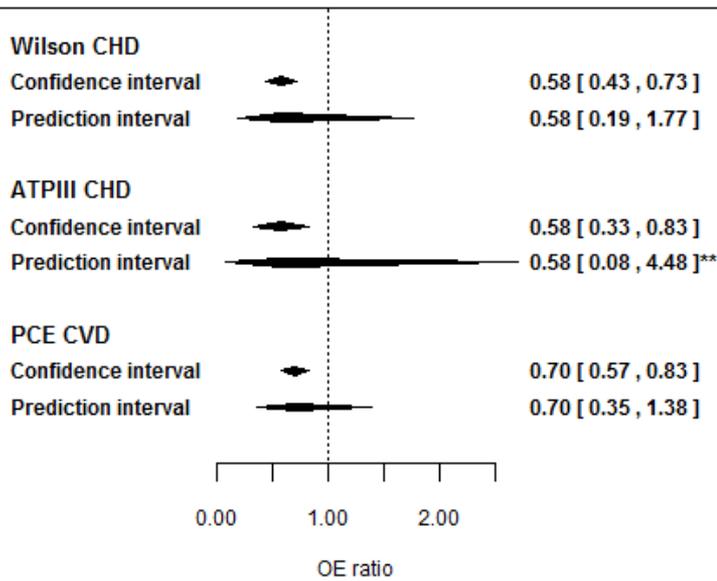
Meta-analysis



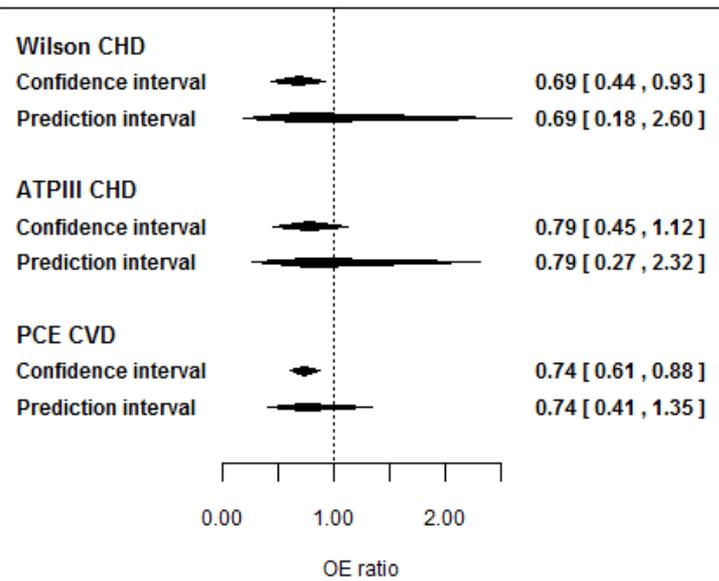
Step 5

Meta-analysis

Men

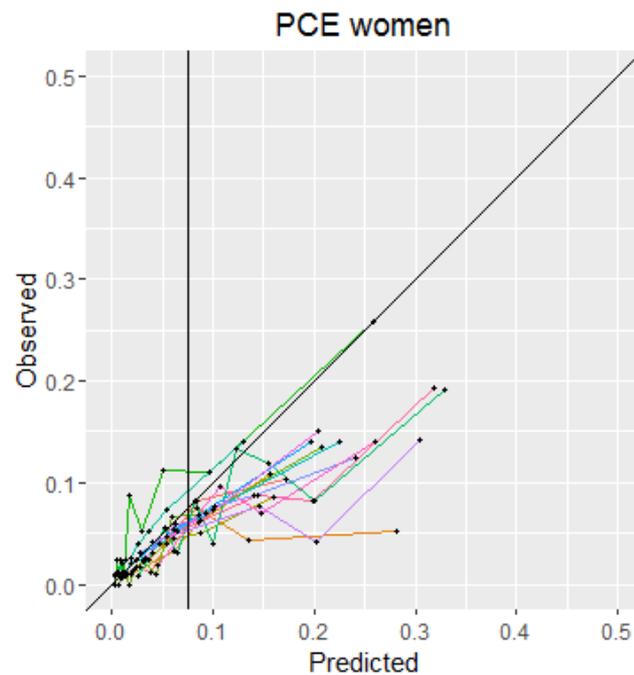
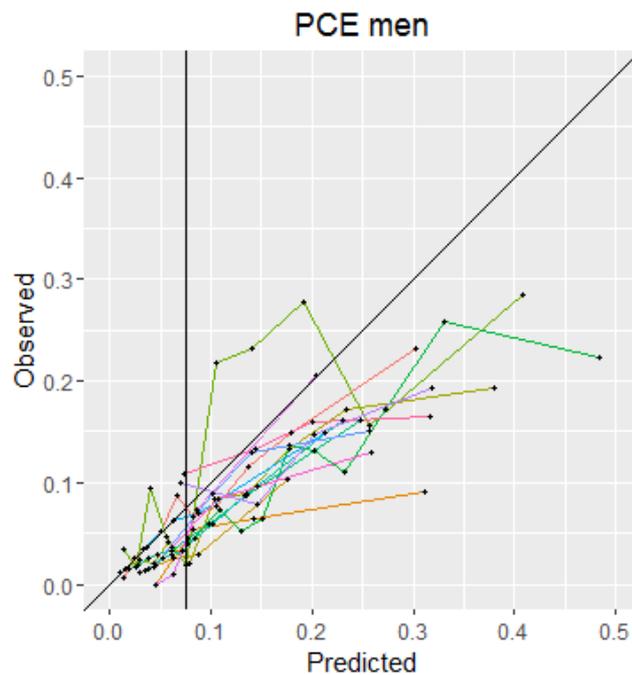


Women



Step 5

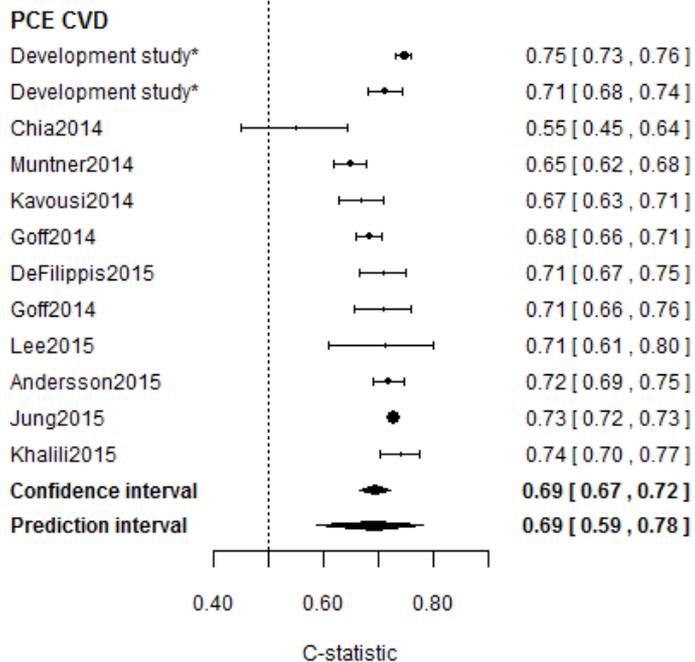
Meta-analysis



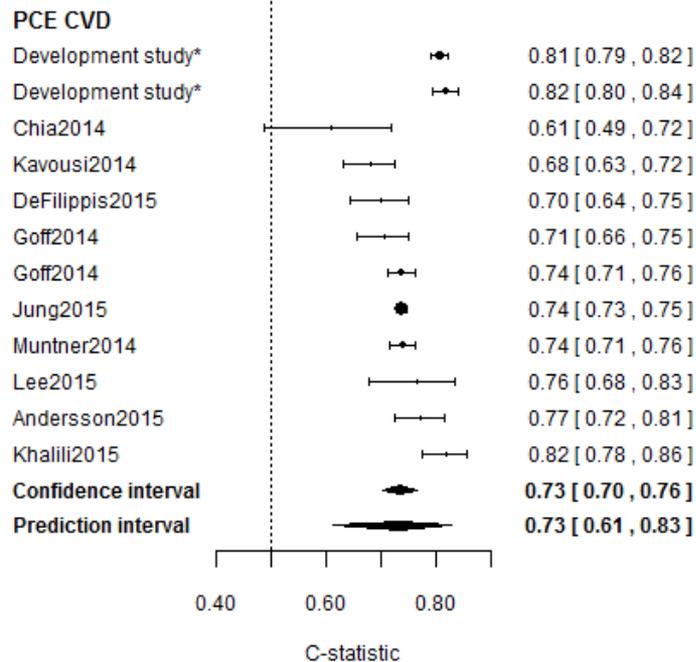
Step 5

Meta-analysis

Men

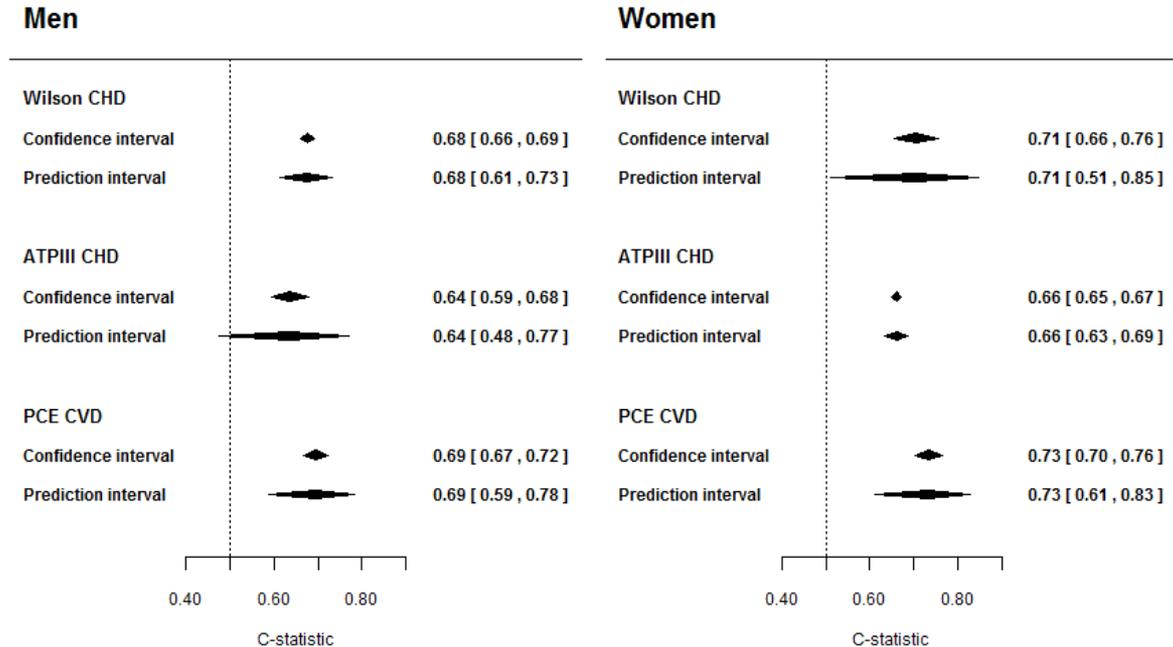


Women



Step 5

Meta-analysis



Step 6

Investigating heterogeneity across studies

OE ratio

- Closer to 1 in US compared to other continents
- No association found for other variables (e.g. eligibility criteria, patient characteristics, year)

C-statistic

- Decrease with higher mean age, mean SBP and lower sd age
- No association found for other variables



Step 7

Sensitivity analyses

		PCE men		PCE women
OE ratio	N	OE (95%CI)	N	OE (95%CI)
All validations	10	0.698 (0.565-0.862)	11	0.742 (0.62-0.888)
Low risk of bias for all domains	2	-	3	-
Weighted by number of events	10	0.698 (0.567-0.86)	11	0.739 (0.619-0.881)
Bivariate analyses	10	0.693 (0.58-0.828)	11	0.739 (0.633-0.863)
Not extrapolated to 10 year	10	0.698 (0.565-0.862)	11	0.742 (0.62-0.888)
C-statistic				
	N	C (95%CI)	N	C (95%CI)
All validations	10	0.694 (0.660-0.726)	10	0.733 (0.695-0.768)
Low risk of bias for all domains	2	-	2	-
Weighted by number of events	10	0.696 (0.664-0.726)	10	0.733 (0.694-0.769)
Bivariate analyses	10	0.695 (0.665-0.724)	11	0.734 (0.703-0.762)



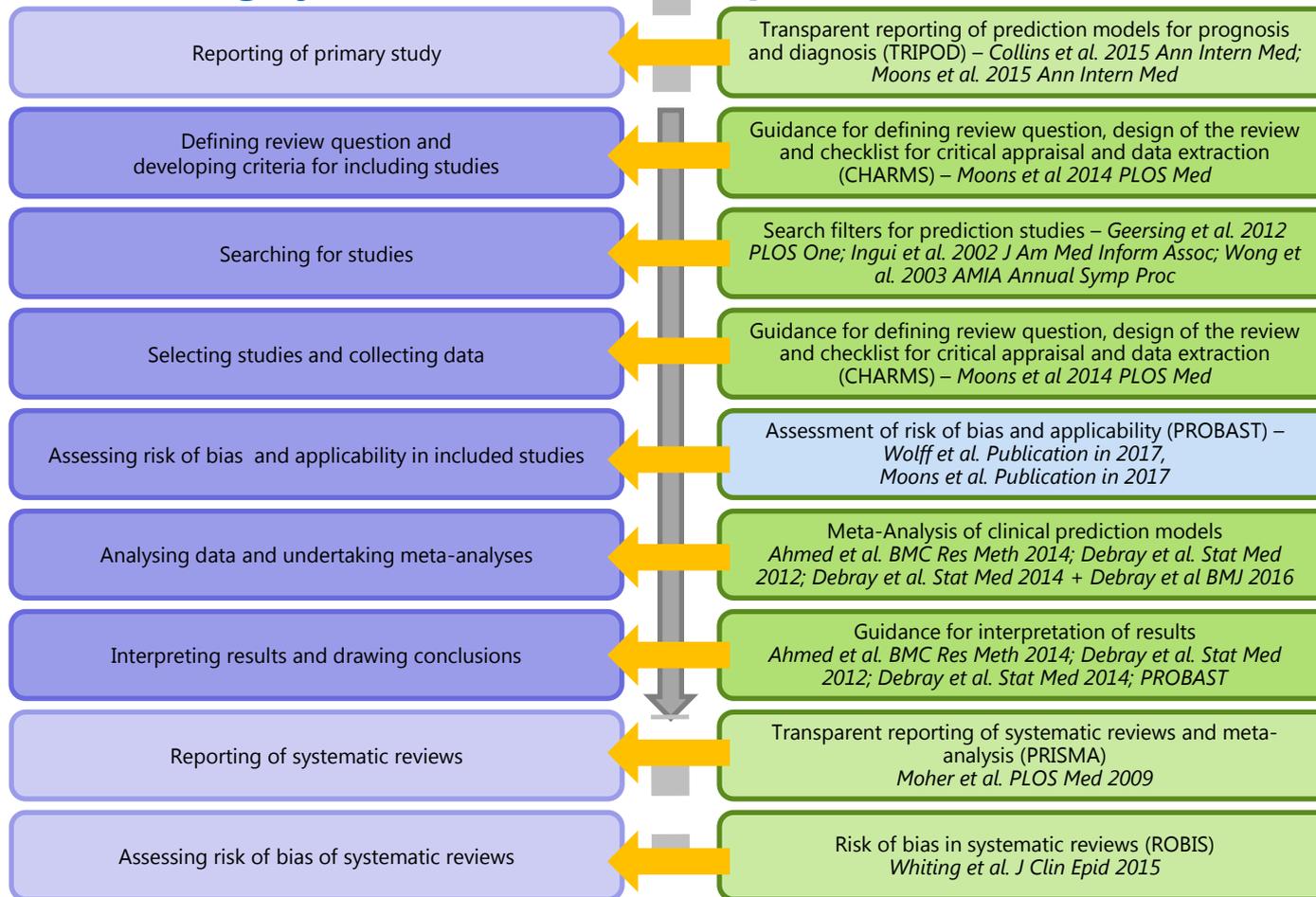
Closing remarks

Closing remarks

- Many similarities to other types of meta-analysis, however,
 - Data extraction more difficult
 - Heterogeneity more common
 - Summary estimates less meaningful
- Need to focus more on
 - Quantifying between-study heterogeneity
 - Assessing sources of variability in model performance



Conducting systematic reviews of prediction model studies



Handy tools/papers

- Debray TPA et al. A new framework to enhance the interpretation of external validation studies of clinical prediction models. *J Clin Epidemiol* 2015.
- Debray TPA et al. A guide to systematic review and meta-analysis of prediction model performance. *BMJ* 2017.
- Debray TPA et al. A framework for meta-analysis of prediction model studies with binary and time-to-event outcomes. *Stat Methods Med Res* 2018.
- Snell KIE et al. Multivariate meta-analysis of individual participant data helped externally validate the performance and implementation of a prediction model. *J Clin Epidemiol* 2015.
- Snell KIE et al. Prediction model performance across multiple studies: which scale to use for the c-statistic and calibration measures? *Stat Met Meth Res* 2017.



Workshop aftercare

- Questions about workshop?
- Assistant needed with review of studies of prognosis studies?
- Visit our website: <https://methods.cochrane.org/prognosis/>
- Please contact:
 - PMG Coordinator: Anneke Damen (CochranePMG@umcutrecht.nl)
 - PMG Co-convenor: Karel Moons (K.G.M.Moons@umcutrecht.nl)

