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

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



## Introduction

- Abundance of published prediction models to estimate absolute risk in individual patients
  - ▶ Cardiovascular disease (> 350 models) 
  - ▶ Traumatic brain injury (> 100 models) 
  - ▶ Breast cancer (> 50 models) 
- External validation studies are increasingly common
  - ▶ Apply published model(s) in new patients
  - ▶ Compare predicted and observed outcomes
  - ▶ Quantify discrimination and calibration performance
  - ▶ TRIPOD guidelines for conduct and reporting

## Introduction

- Estimates of prediction model performance are likely to vary
  - ▶ Sampling error
  - ▶ Differences in predictor effects
  - ▶ Differences in patient spectrum
- Interpretation of validation study results often difficult
  - ▶ Reproducibility of model predictions
  - ▶ Transportability across different settings and populations
- Synthesis of validation studies is needed
  - ▶ To assess the model's likely performance in new settings or populations
  - ▶ To better understand under what circumstances developed models perform adequately or require further adjustments

## Formal guidance for systematic review and meta-analysis

- 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. 
- Implementation in R package metamisc



## Motivating example

### Framingham Risk Score

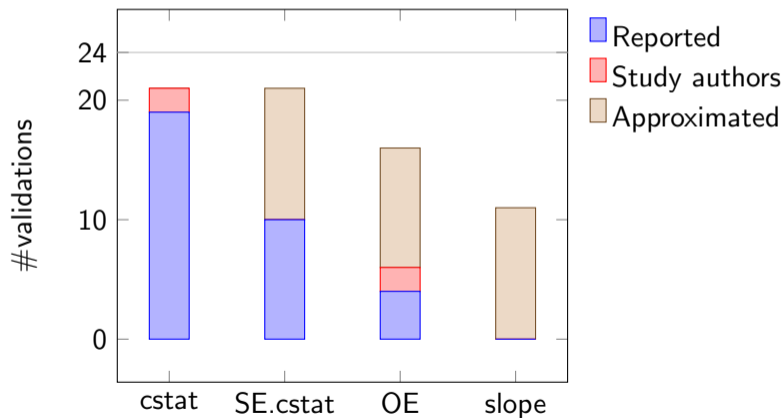
- Model type: Cox regression
- Outcome: Fatal or non-fatal coronary heart disease (CHD)
- Timing: Initial CHD within 10 years
- Evidence: 24 validations in male populations

### Summarize estimates of model performance

- Concordance statistic (*cstat*)
- Ratio of observed versus expected events (*OE*)
- Calibration slope (*slope*)

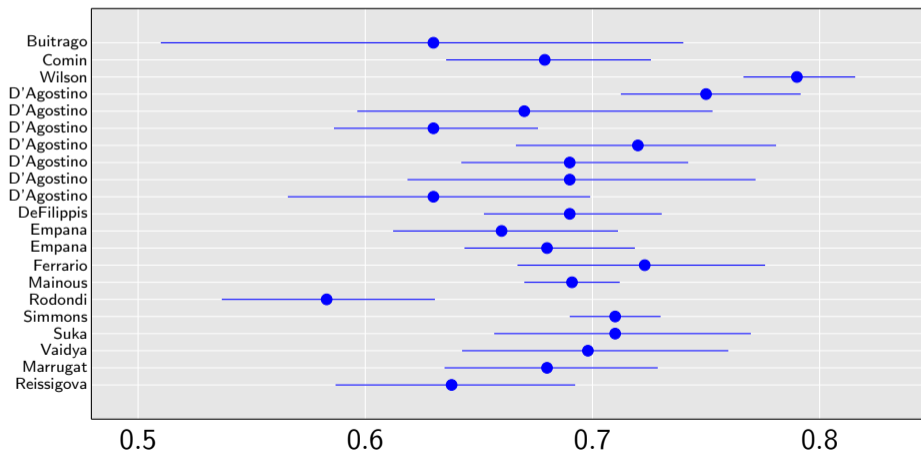
## Data extraction

**Key problem:** Poor and inconsistent reporting of prediction model performance



# Data extraction

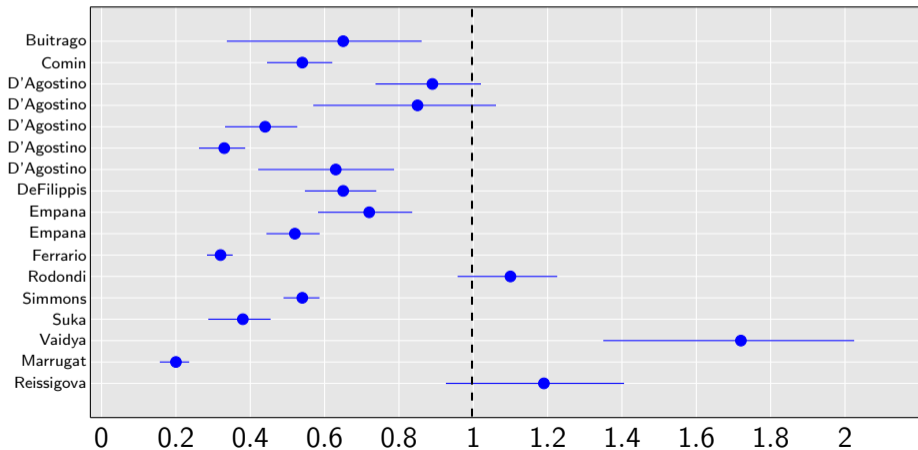
## Concordance statistic with 95% confidence interval



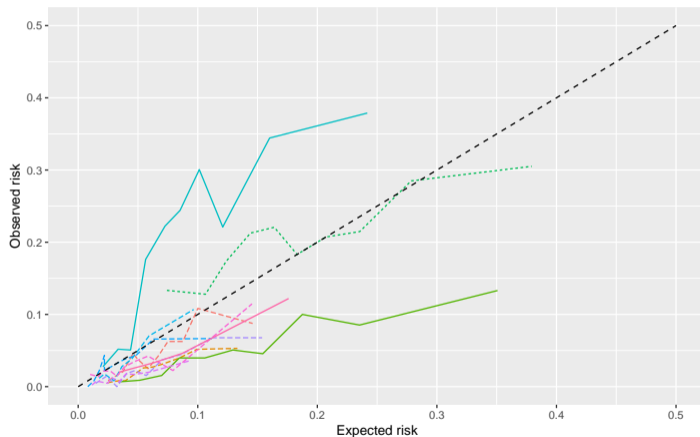


# Data extraction

Ratio of observed vs. expected events with 95% CI



## Data extraction



Risk estimates were reported for 5 (dashed lines), 7.5 (dotted lines) and 10 years follow-up (full lines).

## Meta-analysis of the c-statistic

- Proposed random effects model

$$\text{logit}(c_i) \sim \mathcal{N}(\mu_{\text{discr}}, \text{Var}(\text{logit}(c_i)) + \tau_{\text{discr}}^2)$$

- Weakly informative priors based on empirical data from 26 meta-analyses

Estimation	$K$	Summary	95% CI	95% PI
REML	21	0.69	0.66 – 0.71	0.59 – 0.77
Bayesian (Unif)	24	0.69	0.66 – 0.71	0.59 – 0.78
Bayesian (Student-t)	24	0.69	0.66 – 0.71	0.59 – 0.78

For 3 studies, we did not have information on  $c_i$  but could nevertheless approximate  $\text{SE}(c_i)$ .

## Meta-analysis of the total O:E ratio

- 3 possible random effects models

Option 1  $\ln(\text{O:E})_i \sim \mathcal{N}(\mu_{\text{cal.OE}}, \text{Var}(\ln(\text{O:E})_i) + \tau_{\text{cal.OE}}^2)$

Option 2  $O_i \sim \text{Binom}(N_i, p_{\text{O},i})$

$E_i \sim \text{Binom}(N_i, p_{\text{E},i})$

$\ln(p_{\text{O},i}/p_{\text{E},i}) \sim \mathcal{N}(\mu_{\text{cal.OE}}, \tau_{\text{cal.OE}}^2)$

Option 3  $O_i \sim \text{Poisson}(E_i \exp(\eta_i))$

$\eta_i \sim \mathcal{N}(\mu_{\text{cal.OE}}, \tau_{\text{cal.OE}}^2)$

- Weakly informative priors based on empirical data from 16 meta-analyses

## Meta-analysis of the total O:E ratio

<b>Estimation</b>	<b><i>K</i></b>	<b>Summary</b>	<b>95% CI</b>	<b>95% PI</b>	
REML <sup>1</sup>	6	0.56	0.28 – 1.16	0.09 – 3.62	
Bayesian <sup>1</sup> (Unif)	6	0.61	0.19 – 1.08	0.00 – 2.84	
Bayesian <sup>1</sup> (Student-t)	6	0.61	0.20 – 1.07	0.00 – 2.63	
ML <sup>3</sup>	6	0.56	0.25 – 1.26	0.03 – 11.29	*
Bayesian <sup>3</sup> (Unif)	7	0.60	0.19 – 1.09	0.00 – 2.91	
Bayesian <sup>3</sup> (Student-t)	7	0.60	0.18 – 1.05	0.00 – 2.67	

## Meta-analysis of the calibration slope

- Proposed random effects model

$$O_{ij} \sim \text{Binom}(N_{ij}, p_{O,ij})$$

$$\text{logit}(p_{O,ij}) = \alpha_i + \beta_i \text{logit}(P_{E,ij})$$

$$\beta_i \sim \mathcal{N}(\mu_{\text{cal.slope}}, \tau_{\text{cal.slope}}^2)$$

Estimation	$K$	Summary	95% CI	95% PI
ML	3	1.03	0.90 – 1.16	0.20 – 1.87
Bayesian <sup>†</sup>	3	1.05	0.47 – 1.64	-0.01 – 2.22
Bayesian <sup>‡</sup>	3	1.05	0.51 – 1.65	-0.06 – 2.17

## Final remarks

Meta-analysis of prediction model studies is . . .

- Necessary (inferring on generalizability)
- Feasible (methods, guidance and software available)
- Supported (Cochrane Prognosis Methods Group)