

Evidence synthesis with limited studies

EFSPI Latest Trends in HTA, 15th February 2019

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Motivation

- Evidence can arise from multiple sources in HTA
 - Pairwise meta-analysis (MA), network meta-analysis (NMA)
 - $\circ~$ Fixed effect (FE) and random effects (RE) model
- RE model generally preferred
 - Allow for heterogeneity
 - Generalisable beyond included studies
- Problem: limited number of studies

 Insufficient data to estimate the heterogeneity reliably
- Solution: Bayesian approach
 - What prior?



NICE TA163

- Disease: ulcerative colitis
- Outcome measure: colectomy rate at 3 months

<u>No heterogeneity</u> FE model 0.72 (0.18, 2.70) High heterogeneity RE (vague prior) 0.70 (0.01, 84.6)

Variability of treatment effects among studies





Common scenario

NICE STAs

- The company
 - "very few studies...to support the estimation of a random effects model"
 - o "instability in the WinBUGS model"
 - o "random effects models did not converge"
- Default to the use of a fixed effect model
 - The expert review group (ERG)
 - "too few studies...not a valid reason..."
 - "external information should be used...plausible posterior uncertainty"



Justification of model choice

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NICE STAs (2005-2016)

Method (number of submissions)		Justification	N(%)
Pairwise meta- analysis (38*)	FE model only (7)	No justification	5(71%)
		Check heterogeneity	2(29%)
Network meta- analysis (71 [*])	FE model only (24)	Insufficient data	17(71%)
		No justification	6(25%)
		Check heterogeneity	1(4%)

*: Multiple analyses and analyses for multiple outcomes may have been conducted in one submission.

- Uncertainty: underestimate/overestimate
- How to overcome the problem? • Incorporating external evidence



Currently commonly used external evidence

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- Empirical evidence
 - Turner et al. (2012), Rhodes et al. (2015): predictive distributions for the heterogeneity parameter in various settings using studies from the Cochrane Database of Systematic Reviews
 - Outcomes: binary outcome [Turner et al. (2012)]; standardised mean difference [Rhodes et al. (2015)]
- Other suggested priors
 - Spiegelhalter et al. (2004): Half-Normal (0.51)
 - Friede et al. (2016): Half-Normal (0.5) and Half-Normal (1)
 - NICE DSU TSD 3: Half-Normal (0.32)
 - \circ Outcomes: binary

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Which one to choose?

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Probability Density





Experts' beliefs

- Subjective; controversial; possible to quantify?
- Motivating example 1

TA 163: Colectomy rate at 3 months	OR , median (95% Crl/Prl) infliximab vs. placebo		
RE model	0.70 (0.01, 84.59)	Posterior distribution	
$\tau_{OR} \sim uniform [0, 5]$	0.69 (0, 2498.82)	Predictive distribution	

Don't believe the results (implausible upper limit). \rightarrow RE model should not be used.





Experts' beliefs

- Motivating example 2
 - Spiegelhalter et al. (2004): Half-Normal (0.51)
 - NICE DSU TSD: Half-Normal (0.32)





Elicitation framework ¹⁰

- Aim: Construct a genuine prior distribution for the heterogeneity parameter using external information
 - Empirical evidence: Turner et al. (2012), Rhodes et al. (2015)
 - Experts' beliefs: experts, published opinion

Technical challenges

How to construct probability distributions for abstract model parameters from judgements about interpretable observable quantities

- Elicit the 'range' of treatment effects
- Transform the prior distribution for the 'range' to obtain the prior for the heterogeneity



Notation

• δ_i : treatment effect in study i, for i = 1, ..., S $\circ \log OR$ 11

- log HR
- o mean difference
- $\delta_1, \dots, \delta_S \sim N(d, \tau^2)$



What quantity to elicit?²

- Assume δ_i is log OR
- Quantity of interest

 \circ Heterogeneity parameter, au

- Interpretable observable quantities • Study-specific treatment effect, OR
- Propose to elicit: $R = \frac{OR_{97.5}}{OR_{2.5}}$





How does it work?

$$\delta_{97.5} - \delta_{2.5} = 2 \times 1.96\tau = 3.92\tau$$

$$\rightarrow \log(R) = 3.92\tau$$

$$\rightarrow \tau = \frac{\log(R)}{3.92}$$
(1)

- Make judgements about R, then judgements about τ can be inferred using equation (1)
- Less formal definition of R
 - The ratio of the largest to the smallest OR that could arise over a set of studies
 - The 'range' of treatment effects
 - TA163: R = 10 (The largest OR of having collectomy when comparing infliximab to placebo could be 10 times more than the smallest OR in a population of studies.)



What if?

- Expert is only able to specify a point estimate of *R*
 - No probabilistic distribution
- Expert is not able to say anything about *R*

Three-stage procedure for elicitation





- R package: SHELF
- function: elicitHeterogen()
- See Ren et al. (2018) for details





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probability

0.012

0.856

0.132

0.000



Extensions

• NMA

- \circ Homogeneous variance model
- Elicit the "range" for a pairwise comparison [most comfortable about expression beliefs]
- Feedback on if agree with the elicited probabilities for other pairwise comparisons in the network



Extensions

- Scale-free: hazard ratio, relative risk, ratio of means
 - Three-stage procedure [check if Turner et al. (2012) is also applicable]
- Continuous: Three-stage procedure with modification
 - Dichotomise the response using some appropriate cut-off to define a new treatment effect on the OR scale
 - Three-stage procedure considering ORs
 - Given a prior for τ_{OR} (variability in log ORs), convert it to a prior for τ_{MD} on the original scale via $\tau_{MD} = \omega \tau_{OR}$

$$\circ \omega = \sigma \frac{\sqrt{3}}{\pi}$$

- $\circ \sigma$: an estimate of an individual level SD
- \circ See Ren et al. (2018) for details

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NICE TA163



- Disease: ulcerative colitis
- Outcome measure: colectomy rate at 3 months
- Fixed effect model was used
- Re-analyse using a random effects with
 - $\circ \tau_{OR} \sim U[0, 5]$
 - $\circ \tau_{OR} \sim HN(0.5)$
 - Turner et al. (2012) prior: $\tau_{OR}^2 \sim lognormal(-2.56, 1.74^2)$
 - \circ Truncated Turner et al. (2012): $R_{max} = 10$
 - Elicited prior: $(R_{OR}-1) \sim gamma(2.62, 0.721)$ and $\tau_{OR} = \log(R_{OR})/3.96$



Results (TA163)

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Method	OR median (95% Crl) infliximab vs. placebo	OR median (95% Crl) ciclosporin vs. placebo	Probability of heterogeneity			
			Low	Moderate	High	Extreme
FE	0.72 (0.18, 2.70)	0.13 (0.03, 0.44)	0	0	0	0
RE (vague prior)	0.70 (0.01, 84.59)	0.02 (0, 1.46)	0.01	0.05	0.07	0.87
RE (HN(0.5))	0.71 (0.15, 3.40)	0.12 (0.02, 0.50)	0.15	0.51	0.29	0.05
RE (Turner prior)	0.71 (0.14, 3.25)	0.11 (0.01, 0.48)	0.11	0.62	0.18	0.08
RE (truncated Turner prior)	0.69 (0.17, 2.77)	0.12 (0.03, 0.48)	0.15	0.78	0.07	0
RE (elicited prior)	0.71 (0.17, 2.97)	0.12 (0.03, 0.47)	0.01	0.85	0.14	0



NICE TA336

• Disease: type 2 diabetes mellitus



- Outcome measure: CFB in body weight (kg) at 24 wks
- Fixed effect model was used
- Re-analyse using a random effects with $_{\rm MD}$ ~ U[0, 5]
 - Rhodes et al. (2015) prior: $log(\tau_{SMD}^2) \sim t(-3.44, 2.59^2, 5)$
 - Turner et al. (2012) prior: $\tau_{OR}^2 \sim lognormal(-2.56, 1.74^2)$ and $\tau_{MD} = 2.61 \times \tau_{OR}/1.81$
 - \circ Truncated Turner et al. (2012): $R_{max} = 10$
 - Elicited prior: $(R_{OR}-1) \sim gamma(1.94, 0.741)$ and $\tau_{MD} = 2.61 \times \log(R_{OR})/(3.96 \times 1.81)$



Results (TA336)

MD median	MD median	Probability of heterogeneity			
[95% Crl] Empa vs. placebo	[95% Crl] acebo Empa vs. Linagliptin		Moderate	High	Extreme
-1.77 [-2.18, -1.35]	-2.10 [-2.64, -1.54]	0	0	0	0
-1.76 [-6.10, 2.70]	-2.08 [-8.12, 4.08]	0.14	0.32	0.19	0.35
-1.79 [-2.54, -0.99]	-2.10 [-3.18, -1.01]	0.45	0.45	0.06	0.04
-1.77 [-3.08, -0.45]	-2.10 [-3.94, -0.27]	0.27	0.50	0.14	0.09
-1.77 [-2.88, -0.63]	-2.10 [-3.65, -0.51]	0.18	0.70	0.10	0.02
-1.77 [-2.62, -0.93]	-2.10 [-3.30, -0.93]	0.21	0.75	0.04	0
-1.78 [-2.76, -0.80]	-2.10 [-3.47, -0.72]	0.08	0.88	0.03	0
	MD median [95% Crl] Empa vs. placebo -1.77 [-2.18, -1.35] -1.76 [-6.10, 2.70] -1.79 [-2.54, -0.99] -1.77 [-3.08, -0.45] -1.77 [-2.88, -0.63] -1.77 [-2.62, -0.93] -1.78 [-2.76, -0.80]	MD median [95% Crl] Empa vs. placeboMD median [95% Crl] Empa vs. Linagliptin-1.77 [-2.18, -1.35]-2.10 [-2.64, -1.54]-1.76 [-6.10, 2.70]-2.08 [-8.12, 4.08]-1.79 [-2.54, -0.99]-2.10 [-3.18, -1.01]-1.77 [-3.08, -0.45]-2.10 [-3.94, -0.27]-1.77 [-2.62, -0.93]-2.10 [-3.65, -0.51]-1.78 [-2.76, -0.80]-2.10 [-3.47, -0.72]	MD median [95% Crl] Empa vs. placeboo MD median [95% Crl] Empa vs. Linagliptin Prob. -1.77 [-2.18, -1.35] -2.00 [-2.64, -1.54] 0 -1.76 [-6.10, 2.70] -2.08 [-8.12, 4.08] 0.14 -1.79 [-2.54, -0.99] -2.10 [-3.18, -1.01] 0.45 -1.77 [-3.08, -0.45] -2.10 [-3.94, -0.27] 0.27 -1.77 [-2.88, -0.63] -2.10 [-3.30, -0.93] 0.21 -1.77 [-2.62, -0.93] -2.10 [-3.47, -0.72] 0.08	MD median [95% Crl] Empa vs. placebo MD median [95% Crl] Empa vs. Linagliptin Probability of he Moderate -1.77 [-2.18, -1.35] -2.10 [-2.64, -1.54] 0 0 0 -1.77 [-2.18, -1.35] -2.10 [-2.64, -1.54] 0 0 0 -1.76 [-6.10, 2.70] -2.08 [-8.12, 4.08] 0.14 0.32 0 -1.79 [-2.54, -0.99] -2.10 [-3.18, -1.01] 0.45 0.45 0.45 -1.77 [-3.08, -0.45] 2.10 [-3.94, -0.27] 0.27 0.50 0 -1.77 [-2.88, -0.63] -2.10 [-3.30, -0.93] 0.21 0.75 0.75 -1.78 [-2.76, -0.80] -2.10 [-3.47, -0.72] 0.08 0.88 0.88	MD median [95% Crl] Empa vs. placebo MD median [95% Crl] Empa vs. Linagliptin Probability of heteroge 1.00 Moderate High -1.77 [-2.18, -1.35] -2.10 [-2.64, -1.54] 0 0 0 -1.76 [-6.10, 2.70] -2.08 [-8.12, 4.08] 0.14 0.32 0.19 -1.79 [-2.54, -0.99] -2.10 [-3.18, -1.01] 0.45 0.45 0.06 -1.77 [-3.08, -0.45] -2.10 [-3.65, -0.27] 0.27 0.50 0.14 -1.77 [-2.62, -0.93] -2.10 [-3.30, -0.93] 0.21 0.75 0.04 -1.78 [-2.76, -0.80] -2.10 [-3.47, -0.72] 0.08 0.88 0.03

*: with modification (see Ren et al. (2018))

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Summary

• Use external evidence for τ









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- Use genuine prior distribution for τ
- Minimum requirement: the ratio of the largest to the smallest OR (the 'range' of treatment effects)



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