Methods to describe treatment effect heterogeneity in individual patient data meta-analysis

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Meta-analysis

- Conventional meta-analysis based on summary level data $^1\colon$
	- For every study an estimate of the treatment effect (SD) is available;
	- These treatment effects are pooled to obtain a single summary estimate of the treatment effect (along with CI).
- IPD meta-analysis using individual level data²:
	- These data are pooled either using a two-stage approach (above);
	- Or, the data are analyzed using a one-stage approach using a generalised linear mixed model (details later).
- Two common approaches, fixed or random:
	- Fixed effect meta-analysis (common treatment effect across studies);
	- Random effect meta-analysis (heterogeneity of treatment effects).

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¹ Egger M. Smith GD, Phillips AN. Meta-analysis: principles and procedures. BMJ. 1997

 2 Higgins JP, Whitehead A, Turner RM, Omar RZ, Thompson SG. Meta-analysis of continuous outcome data from individual patients. Stat [Me](#page-0-0)d[. 2](#page-2-0)[0](#page-0-0)[01](#page-1-0) QQ

Treatment effect heterogeneity in meta-analysis

• Test-statistic for treatment effect heterogeneity:

$$
Q = \sum w_i (\hat{\mu}_i - \hat{\mu}_F)^2
$$
 (1)

where i : study; $\hat{\mu}_i$: treatment effect for study i ; w_i : precision for study *i*; $\hat{\mu}_F$: weighted pooled estimate.

If $w_i^{-1} = \hat{\sigma}^2$ (variance of the treatment effect for study i) does not vary across studies the intuitive measure of between study heterogeneity is:

$$
\hat{I}^2 = \frac{\hat{\tau}^2}{\hat{\tau}^2 + \hat{\sigma}^2} = \frac{between}{between + within}
$$
 (2)

where $\hat{\tau}^2$ is the (estimated) variance of the distribution of the μ_i 's across the studies.

If w_i is allowed to vary across studies it turns out that:

$$
\hat{I}^2 = 100 * \frac{Q - (K - 1)}{Q} \tag{3}
$$

where K is the number of studies.

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Finally, the predictive interval, which represents a region in which it is expected that 95% of future trial specific treatment estimates will fall, will be:

$$
[\hat{\mu}_F - t_{\alpha/2,K-1} * \sqrt{((\hat{\tau}^2 + SE(\hat{\mu}_F)^2) \text{ to } \hat{\mu}_F + t_{\alpha/2,K-1} * \sqrt{(\hat{\tau}^2 + SE(\hat{\mu}_F)^2)}]
$$
(4)

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Simulated IPD data (true I-squared 91%)

10 trials; High treatment effect heterogeneity (I-squared $= 87.2\%$; Q-statistic $=$ 70.13 (d.f $=$ 9) p $=$ 0.000; $\hat{\tau}^2=$ 0.14); two-stage approach.

We will go on to consider how this analysis could be conducted using a one-stage approach.

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Linear mixed model with treatment effect heterogeneity

Model treatment effect heterogeneity using an "interaction" term and allowing for a covariance term:

$$
y_{ijs} = \beta_0 + x_{ijs}\theta + \alpha(S)_j + x_{js}\alpha(ST)_j + e_{ijs}
$$
(5)

 $|i:$ individual; $j:$ study; $s:$ arm $(m$ per arm) $|$

and that

$$
\left(\begin{array}{c} \alpha(S)_j \\ \alpha(ST)_j \end{array}\right) \sim N\left(\left(\begin{array}{c} 0 \\ 0 \end{array}\right),\left(\begin{array}{cc} \tau_S^2 & \sigma_{ST}^2 \\ \sigma_{ST}^2 & \tau_{ST}^2 \end{array}\right)\right)
$$

S : Study effect; ST : Study by Treatment effect

Relationship to MA

 τ_{ST}^2 represents the variation between studies in their response to treatment (and so is akin to τ^2 in a meta-analysis).

³Hemming K, Taljaard M, Forbes A. Modeling clustering and treatment effect heterogeneity in parallel and stepped-wedge cluster rando[mi](#page-4-0)z[ed](#page-15-0) [t](#page-4-0)[ria](#page-5-0)[ls](#page-6-0)[.](#page-0-0) [S](#page-1-0)[ta](#page-15-0)[t](#page-0-0) [M](#page-1-0)ed[. 2](#page-0-0)[018](#page-15-0) $\alpha \sim$

Recap: I-squared

The between study variability of the treatment effect divided by the sum of the between-study variability and the within-study variability

When analysing using a one-stage approach an intuitive estimate of I-squared is thus:

$$
I^2 = \frac{\tau_{ST}^2}{\tau_{ST}^2 + \frac{2\sigma_e^2}{\bar{m}}}
$$

 m : average (harmonic mean) study size per – arm

Prediction interval:

$$
[\hat{\theta}-t_{\alpha/2,K-1}\sqrt{((\hat{\tau}_{ST}^2+SE(\hat{\theta})^2)\text{ to }\hat{\theta}+t_{\alpha/2,K-1}\sqrt{(\hat{\tau}_{ST}^2+SE(\hat{\theta})^2})]
$$
(6)

Recap: Simulated IPD meta-analysis

10 trials; High treatment effect heterogeneity (True I-squared $= 91\%$; Q-statistic=70.13 $(d.f = 9)p = 0.000; \ \hat{\tau}^2 = 0.14);$

I-squared

Using one-stage approach \hat{l}^2 is 91.7% (87% using two-stage approach).

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Simulation study

- **•** Performance measures: correlation and bias:
- \bullet $N = 10,000$ data-sets simulated for each scenario;
- Data simulated from a linear mixed model with random study and random study by treatment interaction.
- **•** Scenarios considered: 108:
	- REML and DL methods:
	- Number of studies: 10, 50, 100;
	- Study size per arm: 10, 50, 100;
	- Treatment effect 0; total variance 1;
	- Varying study sizes (zero-truncated negative binomial, $CV=0.7$);
	- Approximate (true) I-squared's high: 80% to $97\%^{1/2}$; moderate: 60% to 75%^{2 3}; low: 5% to 20% ^{3 4}.

¹Equivalent $\tau_{CT}^2 = 0.25$; $\tau_C^2 = 0.125$; $\sigma_e^2 = 0.625$. ² Equivalent $\tau_{CT}^2 = 0.125$; $\tau_C^2 = 0.125$; $\sigma_e^2 = 0.75$. ³ Equivalent $\tau_{CT}^2 = 0.025$; $\tau_C^2 = 0.125$; $\sigma_e^2 = 0.85$. ⁴ Equivalent $\tau_{CT}^2 = 0.0025; \ \tau_C^2 = 0.125; \ \sigma_e^2 = 0.8725.$ Ω

Correlation between I-squared one-stage and I-squared two-stage

- Good correlation in large samples or when I-squared high 1 ;
- Models failed to converge for some scenarios with very low l^2 .

 1 Austin (2018) The effect of number of [clus](#page-8-0)t[er](#page-10-0)s and cluster [s](#page-8-0)[ize](#page-9-0) [o](#page-10-0)[n](#page-0-0)[sta](#page-15-0)[ti](#page-0-0)[s](#page-1-0)[tica](#page-15-0)[l p](#page-0-0)[ow](#page-15-0)er. \sim Karla Hemming, Jim Hughes, Andrew Forbes, John Hughes, John May 7, 2021 10/16

No clear method preferable

I-squared known to exhibit bias (upward for low I-squared, downward for high I-squared) 1 ; no clear differences identified between two metrics.

Graphs by Number per arm and Number studies per arm

 1 The heterogeneity statistic I2 can be biased in small meta-analyses Paul T von Hippel BMC Med Res Methodol. 2015; ∢ ロ ▶ . ∢ 伺 ▶ . ∢ ヨ ▶ . ∢

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Points for discussion

- Quantifying treatment effect heterogeneity:
	- Caution: Low I-squared can indicate no treatment heterogeneity or insufficient evidence to make conclusive statements.
	- Caution: High I-squared can indicate clinically important treatment effect heterogeneity or very large sample sizes $^1.$
	- Caution: I-squared can provide ball-park descriptions of magnitude of heterogeneity; best used in conjunction with a predictive interval.
- The proposed I-squared has the potential to be used in:
	- In cluster trials where treatment is crossed with cluster (to describe treatment effect heterogenity across clusters);
	- In individually randomised trials (to describe treatment effect heterogeneity across sites).

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¹Rucker G, Schwarzer G, Carpenter JR, Schumacher M. Undue reliance on I2 in assessing heterogeneity may mislead BMC Med Res Methodol. 2008

 2 Chen B, Benedetti A. Quantifying heterogeneity in individual participant data neta-analysis with binary outcomes Syst Rev. 2017; 6: 2[43](#page-10-0).

Thank you!

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Poor man's estimate of the variance of the average within cluster treatment effect

Recall, for trials where treatment is crossed with cluster:

$$
I^2 = 100 * \frac{\tau^2}{\tau_{CT}^2 + \frac{4\sigma_e^2}{5\bar{m}}}
$$

The (average) within-cluster estimate of the variance of the treatment effect is estimated by:

$$
\frac{4\sigma_e^2}{S\bar{m}}
$$

But....

Whilst this is correct for large sample continuous outcomes where there are no time effects, it should ideally be the average of the variance of within-cluster treatment effects. These are not a direct estimate of the modeling.

Bland Altman plot

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Recall, for trials where treatment is crossed with cluster:

$$
I^{2} = 100\% * \frac{\hat{\tau}_{CT}^{2}}{\hat{\tau}_{CT}^{2} + \hat{\sigma}_{e}^{2} \sum_{j} \frac{1}{\bar{m}_{j}} (\frac{1}{s_{j}} + \frac{1}{(S - s_{j})})}
$$
(7)

where s_i denotes the number of time periods that cluster j is observed under the intervention condition.