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## Guidance paper

### Tutorial

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Research  
Synthesis Methods  
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### Get real in individual participant data (IPD) meta-analysis: a review of the methodology

Thomas P. A. Debray,<sup>a,b\*</sup> Karel G. M. Moons,<sup>a,b</sup>  
Gert van Valkenhoef,<sup>c</sup> Orestis Efthimiou,<sup>d</sup> Noemi Hummel,<sup>e</sup>  
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on behalf of the GetReal methods review group



## IPD-MA of RCTs: two-stage meta-analysis

Valentijn de Jong<sup>1,2</sup>, PhD

1. Julius Center for Health Sciences and Primary Care
2. Data Analytics and Methods Task Force, European Medicines Agency



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## Remainder of this lecture

### Overview of statistical methods

- Summarizing treatment effect(s)
- Investigating subgroups
- Exploring treatment effect modifiers



## Two-stage IPD-MA

Part I: Introduction



MC Utrecht

## Generating aggregate data

- **Continuous outcomes**
  - Mean treatment difference (linear regression)
- **Binary outcomes**
  - Odds ratio (logistic regression)
  - Relative risk (loglinear regression)
- **Time-to-event data**
  - Hazard ratio (Cox regression)



## Approaches for IPD-MA

Two alternate approaches exist to summarize the evidence from multiple studies:

- **Two-stage meta-analysis**  
Analyze each study separately and pool the resulting estimates using standard meta-analytic techniques
- **One-stage meta-analysis**  
Analyze IPD from all studies simultaneously by adopting a statistical model that accounts for clustering among patients



## The procedure

**Step 1:** Analyze each trial individually to reduce the IPD to relevant summary data (aggregate data; AD)

- Estimates of relative treatment effect
- Estimates of treatment-covariate interaction
- Other...

with corresponding estimates of precision

**Step 2:** Summarize the generated AD using traditional meta-analysis methods

- Fixed effect
- Random effects



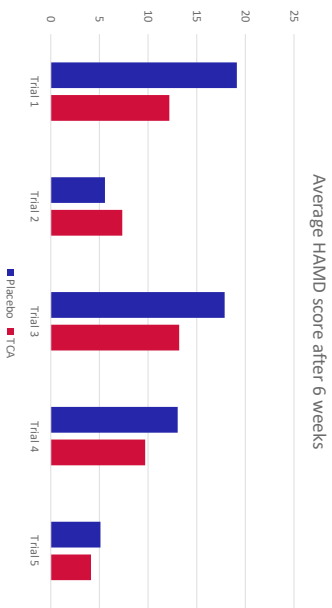
Clinical example

Meta-analysis of antidepressant trials

- 5 randomized trials
  - Patients diagnosed with major depressive disorder
  - Tricyclic antidepressant (TCA) versus Placebo (Plac)
- Outcome measurements
  - Hamilton Depression (HAMd) score, ranging from 0 to 54
  - Measured at baseline and after 6 weeks



Clinical example



Generating aggregate data in RCTs

Treatment effect estimates should be adjusted for a priori specified covariates.

- Randomization does not ensure balance for any particular covariate
- Covariate adjustment results in greater efficiency for testing treatment effect

Refs:

<https://doi.org/10.2307/1403444>  
<https://doi.org/10.1016/j.jclinepi.2003.09.014>  
<https://doi.org/10.1002/jsm.1384>



Clinical example

How would you analyze the IPD from the antidepressant trials?



| Patient | Study | Treatment | HAMd0 | HAMd6 |
|---------|-------|-----------|-------|-------|
| 1       | 1     | Placebo   | 26    | 15    |
| 2       | 1     | TCA       | 24    | 18    |
| 3       | 1     | Placebo   | 29    | 19    |
| ...     |       |           |       |       |
| 439     | 5     | TCA       | 21    | 22    |
| 440     | 5     | placebo   | 24    | 15    |



# Clinical example

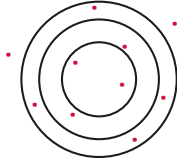
Mean treatment difference of HAMD score after 6 weeks

| Trial | N  | $\delta$ | SE( $\delta$ ) |
|-------|----|----------|----------------|
| 1     | 51 | -6.90    | 2.05           |
| 2     | 53 | 3.40     | 1.03           |
| 3     | 78 | -4.67    | 1.57           |
| 4     | 63 | -3.34    | 1.75           |
| 5     | 16 | -0.97    | 2.16           |

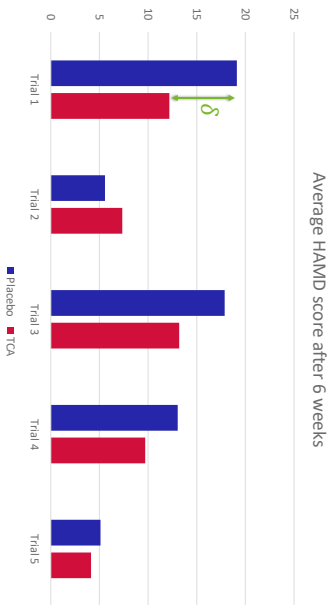
What are possible reasons for differences in estimated treatment effects?



# Fixed effect meta-analysis



# Clinical example



In each trial, we can fit a linear regression model with  $HAMD_6 = \alpha + \beta HAMD_0 + \delta TREAT + \epsilon_i$



# Summarizing the aggregate data

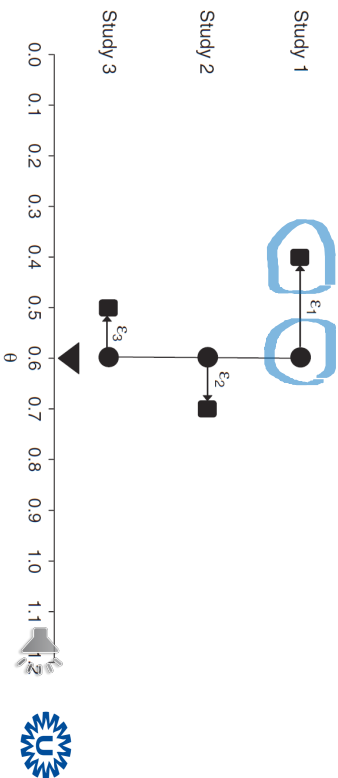
If the primary interest is to obtain summary estimates of comparative treatment effect, we have 2 options to summarize estimates of  $\delta$ :

- **Fixed effect meta-analysis**  
Assumes that all trials estimate the same underlying treatment effect
- **Random effects meta-analysis**  
Assumes that there is a distinct treatment effect in each trial due to the presence of between-study heterogeneity.



### Fixed effect meta-analysis

It is assumed that for all trials, the underlying treatment effect is the same. The only source of variation is estimation error ( $\epsilon$ ) due to limited sample size.



### Fixed effect meta-analysis

We can derive the fixed effect summary  $\bar{D}_F$  as follows:

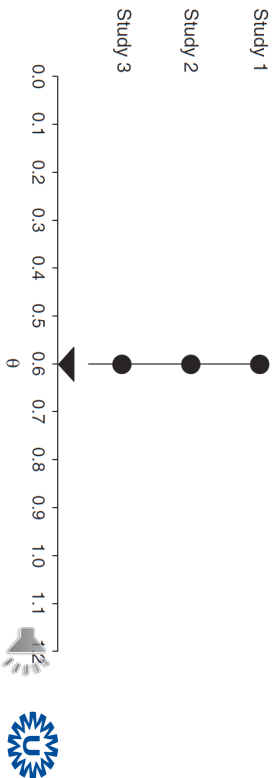
$$\bar{D}_F = \frac{\sum_{k=1}^K \hat{\theta}_k w_k}{\sum_{k=1}^K w_k} \quad \text{and} \quad \text{var}(\bar{D}_F) = \frac{1}{\sum_{k=1}^K w_k}$$

with  $w_k = \frac{1}{V(\hat{\theta}_k)}$  and  $K$  the total number of trials.



### Fixed effect meta-analysis

It is assumed that for all trials, the underlying treatment effect is the same



### Fixed effect meta-analysis

The pooled estimate is an average of all comparative treatment effects, weighted by their precision:

$$\hat{\theta}_k \sim N(D_F, V(\hat{\theta}_k))$$

Where  $\hat{\theta}_k$  represents the estimated treatment effect of study  $k$ , with error variance  $V(\hat{\theta}_k)$ . The pooled treatment effect is given by  $D_F$ .



Solution

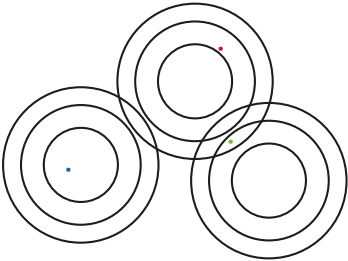
| Trial | N  | $\delta$ | SE( $\delta$ ) |
|-------|----|----------|----------------|
| 1     | 51 | -6.42    | 1.35           |
| 2     | 53 | 1.24     | 1.22           |
| 3     | 78 | -6.88    | 1.04           |
| 4     | 63 | -3.22    | 1.50           |
| 5     | 16 | -0.90    | 3.09           |

$$\hat{d}_F = \frac{\left(\frac{-6.42}{1.35^2} + \frac{1.24}{1.22^2} + \frac{-6.88}{1.04^2} + \frac{-3.22}{1.50^2} + \frac{-0.90}{3.09^2}\right)}{(1.35^{-2} + 1.22^{-2} + 1.04^{-2} + 1.50^{-2} + 3.09^{-2})} = -3.92$$

$$SE(\hat{d}_F) = \sqrt{\frac{1}{(1.35^{-2} + 1.22^{-2} + 1.04^{-2} + 1.50^{-2} + 3.09^{-2})}} = 0.61$$



Random effects meta-analysis



Example

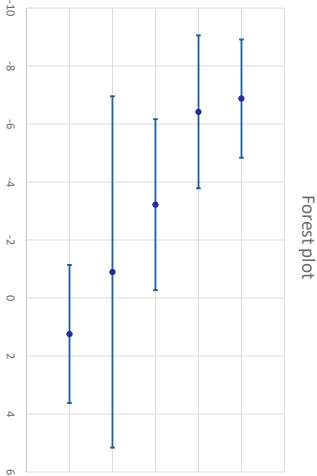
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| 5     | 16 | -0.90    | 3.09           |

How to perform a fixed effect meta-analysis on the comparative treatment effects of TCA versus Placebo?



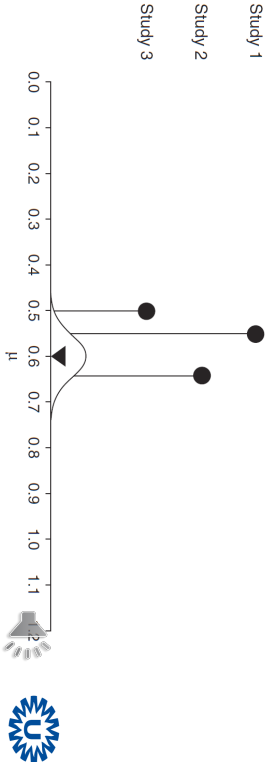
Clinical example

Do you think there is evidence of between-study heterogeneity?



# Random effects meta-analysis

It is assumed that for all trials, there is a distribution of true effects. We are interested in estimating the mean and variance of this distribution



# Random effects meta-analysis

We now have:

$$\begin{aligned}\theta_k &\sim N(\delta_k, V(\theta_k)) \\ \delta_k &\sim N(D, \tau^2)\end{aligned}$$

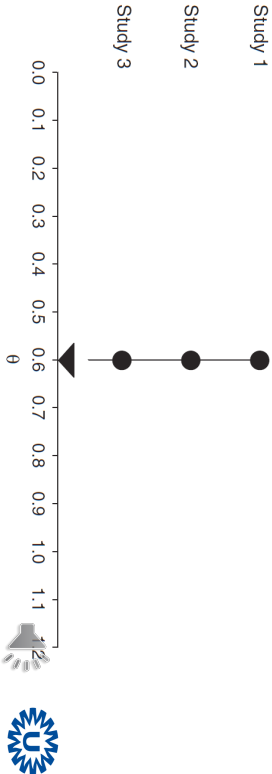
With

- $V(\theta_k)$  the within-study error variance
- $V(D) = \tau^2$  the between-study variance



# Recall: fixed effect meta-analysis

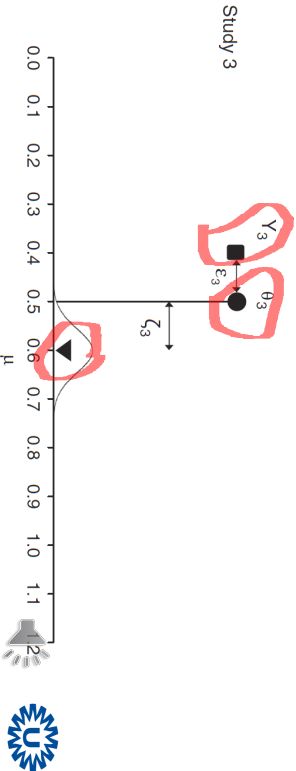
It is assumed that for all trials, the underlying treatment effect is the same



# Random effects meta-analysis

The meta-analysis accounts for 2 sources of variation:

- Estimation error within studies ( $\epsilon$ )
- True variation in effect sizes between studies ( $\zeta$ )



# Clinical example

Mean treatment difference of HAMD score after 6 weeks

| Meta-analysis  | $\bar{D}$ | $se(\bar{D})$ | $\hat{\tau}^2$ |
|----------------|-----------|---------------|----------------|
| Fixed effects  | -3.92     | 0.61          | 0              |
| Random effects | -3.44     | 1.60          | 11.05          |

Do you still think there is evidence of relative efficacy?



# Random effects meta-analysis

We can derive the summary treatment effect as follows:

$$\bar{D}_R = \frac{\sum_{k=1}^K \hat{\theta}_k w_k^*}{\sum_{k=1}^K w_k^*} \quad \text{and} \quad \text{var}(\bar{D}_R) = \frac{1}{\sum_{k=1}^K w_k^*}$$

$$\text{with } w_k^* = \frac{1}{v(\hat{\theta}_k) + \hat{\tau}^2}$$

In the DerSimonian and Laird approach,  $\tau^2$  is estimated from the fixed effect meta-analysis model:  $\hat{\tau}^2 = \frac{Q - df}{C}$ ,  $Q = \sum_{k=1}^K \frac{(\hat{\theta}_k - \bar{D}_R)^2}{v(\hat{\theta}_k)}$ ,  $df = K - 1$  and  $C = \sum_{k=1}^K w_k - \left( \sum_{k=1}^K w_k / \sum_{k=1}^K w_k \right)$



# Prediction interval

We can derive an approximate 95% prediction interval, which provides a range for the true treatment effect in a new study population:

$$\bar{D}_R \pm t_{K-2} \sqrt{\hat{\tau}^2 + \text{var}(\bar{D}_R)}$$

$t_{K-2}$  is the 100(1 -  $\alpha/2$ ) percentile of the  $t$  distribution with  $K-2$  degrees of freedom, where  $K$  is the number of studies in the meta-analysis and  $\alpha/2$  is usually chosen as 0.05/2, to give a 5% significance level and thus 95% prediction interval.

Note that the prediction interval can be calculated more accurately within a Bayesian framework (as it allows for estimation error of  $\hat{\tau}^2$ )



# Random effects meta-analysis

Is it sufficient to simply estimate  $\bar{D}_R$  and its standard error?

- Usually not: the summary estimate (and its confidence interval) does not give any indication about the possible impact of between-study heterogeneity





Solution

Mean treatment difference of HAMD score after 6 weeks

| Meta-analysis  | $\bar{D}$ | SE( $\bar{D}$ ) | $\hat{\tau}^2$ |
|----------------|-----------|-----------------|----------------|
| Fixed effects  | -3.92     | 0.61            | 0              |
| Random effects | -3.44     | 1.60            | 11.05          |

$$-3.44 \pm t_{3, 0.05/2} \sqrt{11.05 + 1.60^2} = [-15.19; 8.30]$$



Note

What if we pool trials with slightly different interventions, and the estimated effect is statistically significant?

- $H_0$  = For each of the pooled trials, the treatment is equal to control.
- $H_a$  = At least one of the pooled interventions is different from control. (Not all of them!)

Simon S. S. Schmidt, S. Schmidt, A. A. A. A note regarding alternative explanations for heterogeneity in meta-analysis. Statistics in Medicine 2009;28(10):1000-1005. doi:10.1002/sim.3600



Example

Mean treatment difference of HAMD score after 6 weeks

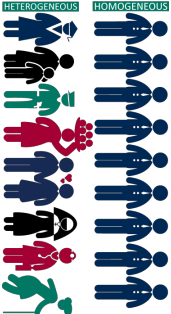
| Meta-analysis  | K | $\bar{D}$ | SE( $\bar{D}$ ) | $\hat{\tau}^2$ |
|----------------|---|-----------|-----------------|----------------|
| Fixed effect   | 5 | -1.47     | 0.69            | 0              |
| Random effects | 5 | -2.67     | 1.58            | 9.5            |

Calculate the 95% prediction interval for the relative treatment effect of TCA.



Possible causes of heterogeneity

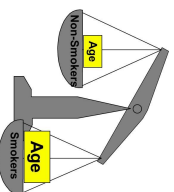
- Publication bias
- Variation in study protocols
- Variation in study quality
- Differences in interventions received (e.g. dose)
- Differences in follow-up length
- Treatment-covariate interaction



## Treatment-covariate interaction

The relative treatment effect varies according to the level of a covariate

- Trial-level interaction: interaction between treatment and a study-level covariate
- Patient-level interaction: interaction between treatment and a patient-level covariate (*effect modification*)



## Meta-regression

- **Step 1:** reduce the IPD to aggregate data
  - Estimate relative treatment effect
  - Extract study characteristics (e.g. level of blinding)
  - Calculate summarized subject-level characteristic (e.g. mean age)
- **Step 2:** meta-analyze the aggregate data using traditional meta-analysis models that adjust for covariates.



## Other causes of heterogeneity

- **Non-collapsibility:** Odds ratios (and hazard ratios) differ depending on the choice of covariate adjustment, levels of the exposure compared, and population over which the comparison is made.



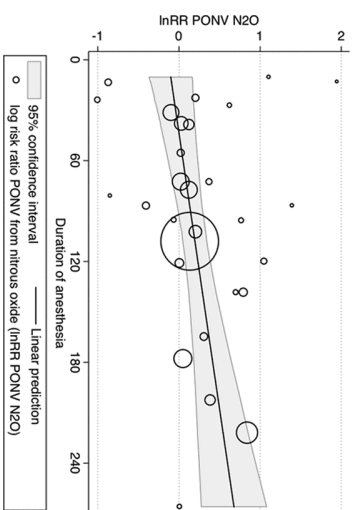
## Investigating heterogeneity

- 2 approaches possible in two-stage meta-analysis
- Meta-regression
  - Pooling of within-trial covariate interactions



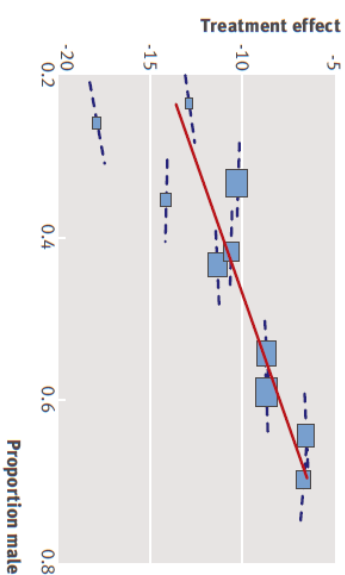
**Ref:** <https://doi.org/10.1080/03610926.2015.1006778>

# Meta-regression



The relationship between the log risk ratio for postoperative nausea and vomiting from nitrous oxide (lnRR PONV<sub>N2O</sub>) and duration of exposure to nitrous oxide (N<sub>2</sub>O) as a bubble plot. The meta-regression line of best fit (linear prediction) and upper and lower 95% CIs are shown. Bubble size is inversely proportional to the standard error of the log risk ratio in each study.  
**Ref:** Nitrous Oxide-related Postoperative Nausea and Vomiting Depends on Duration of Exposure Anesthesiology. 2014;120(6):1137-1145.

# Ecological bias



**Fig 3 |**An example of ecological bias within an aggregate data meta-analysis

# Meta-regression

The meta-analysis model is extended with a (usually centered) study-level covariate  $S_k$ :

$$\begin{aligned}\hat{\delta}_k &\sim N(\mu_k, V(\hat{\delta}_k)) \\ \mu_k &= m_k + \beta S_k \\ m_k &\sim N(M, \tau^2)\end{aligned}$$

The summary estimate  $M$  is now dependent on the value of  $S$

# Meta-regression

## Characteristics

- Investigates heterogeneity due to trial-level interaction (modif. of treatment effect by a specific study-level covariate)
- Low statistical power for identifying effect modifiers
- May lead to ecological (aggregation) bias
  - Associations between aggregated values may not be representative for individual subjects

## Pooling of within-trial covariate interactions

**Step 1:** In each trial, estimate the following model:

$$HAMD_{6i} = \alpha + \delta TREAT_i + \gamma HAMD_{0i} + \theta TREAT_i HAMD_{0i} + \epsilon_i$$

- Step 2:**
- Meta-analysis of  $\delta$  using traditional meta-analysis methods.



## Fixed effect versus random effect

**Arguments against the use of fixed effect**

- It is often unrealistic to assume that all studies estimate the same treatment effect



## Pooling of within-trial covariate interactions

It is generally recommended to use IPD and investigate the presence of subject-level interaction

- **Step 1:**
  - Estimate relative treatment effect, adjusted for interaction effect with modifier of interest
- **Step 2:**
  - Meta-analyze estimates of relative treatment effect (and interaction effect) using traditional meta-analysis methods.



## Recommendations



## Fixed effect versus random effects

**We need advanced estimation methods for performing a random effects meta-analysis**

- Heterogeneity
- Confidence intervals

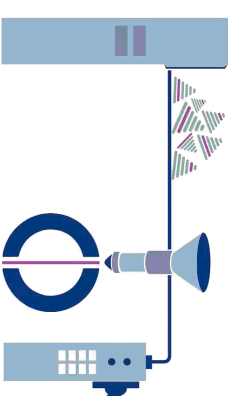
!! For most software packages, if you didn't specify anything, it is most likely that you are using obsolete methods



## Recommendations

#1

Identify studies through systematic review



## Fixed effect versus random effects

**Arguments against the use of random effects**

- Down-weighting of larger studies
- Potential presence of publication bias
- Interpretation of summary estimate



## Estimating heterogeneity

**It turns out many options already exist!!**

- DerSimonian & Laird (DL)
- Maximum Likelihood (ML)
- Restricted Maximum Likelihood (REML)
- Paule & Mandel (PM)
- Hartung & Makambi (HM)
- Sidik & Jonkman (SJ)
- Bayesian model
- ...



## Recommendations

#2

If heterogeneity is present

- The random-effects estimate should be interpreted differently from the fixed effect estimate
- Focusing on the mean is insufficient, and the effect of heterogeneity should be quantified (e.g. prediction intervals)
- Explore possible causes of heterogeneity (more about this later!)



## Recommendations

#4

When calculating confidence intervals

- Adjust the standard error of the summary estimate using the method proposed by Hartung-Knapp-Sidik-Jonkman
- Use a Student T distribution (instead of a Normal distribution)

Inthout et al. The Hartung-Knapp Sidik-Jonkman method for random effects meta-analysis is straightforward and considerably outperforms the standard DerSimonian-Laird method. *BMC Med Res Meth* 2014



## Recommendations

#2

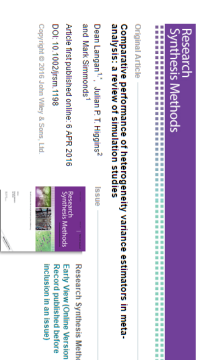
Allow for heterogeneity



## Recommendations

#3

- Adopt the REML or Paule-Mandel method for estimating the heterogeneity variance  $\tau^2$
- Use this variance to estimate the summary effect



# Recommendations

#5

Forget about #3 and #4, and implement a Bayesian meta-analysis model instead

