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Estimating Interactions and Subgroup-Specific Treatment Effects in Meta-Analysis Without Aggregation Bias: A Within-Trial Framework

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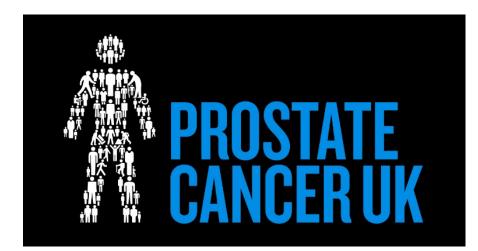
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• Peter Godolphin: No disclosures



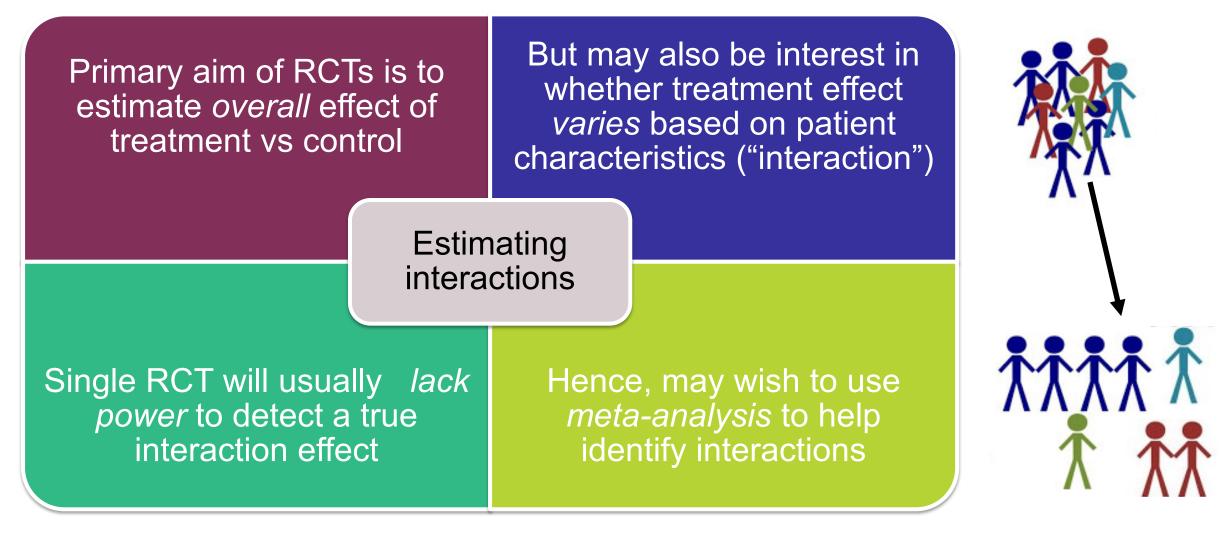
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- Funders: Prostate Cancer UK, UK National Institute for Health Research



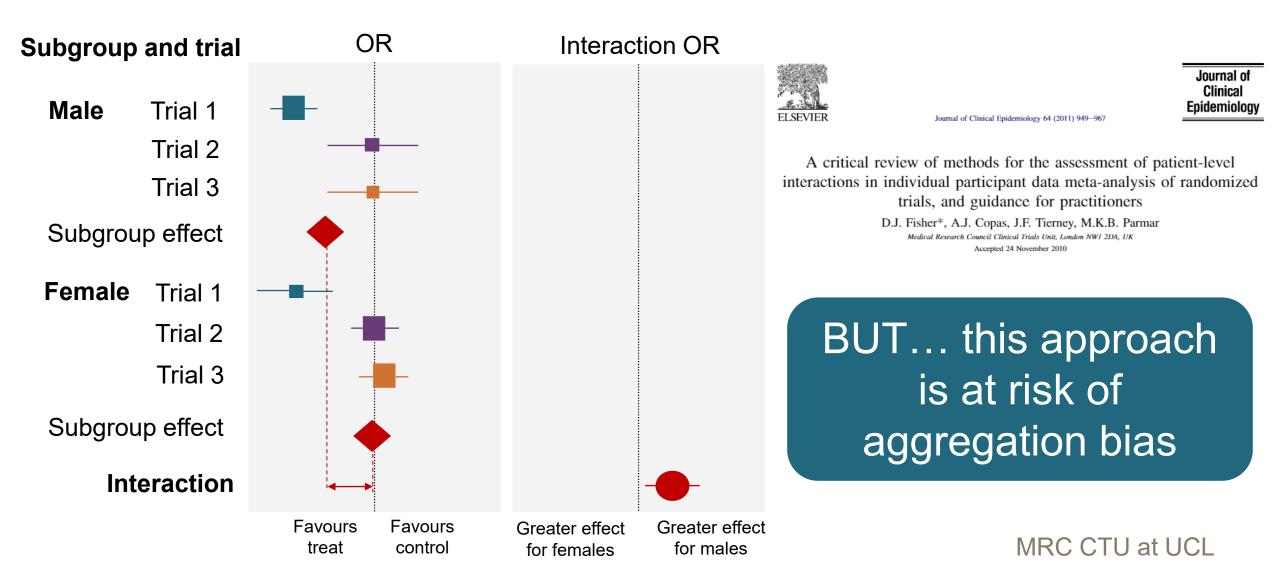
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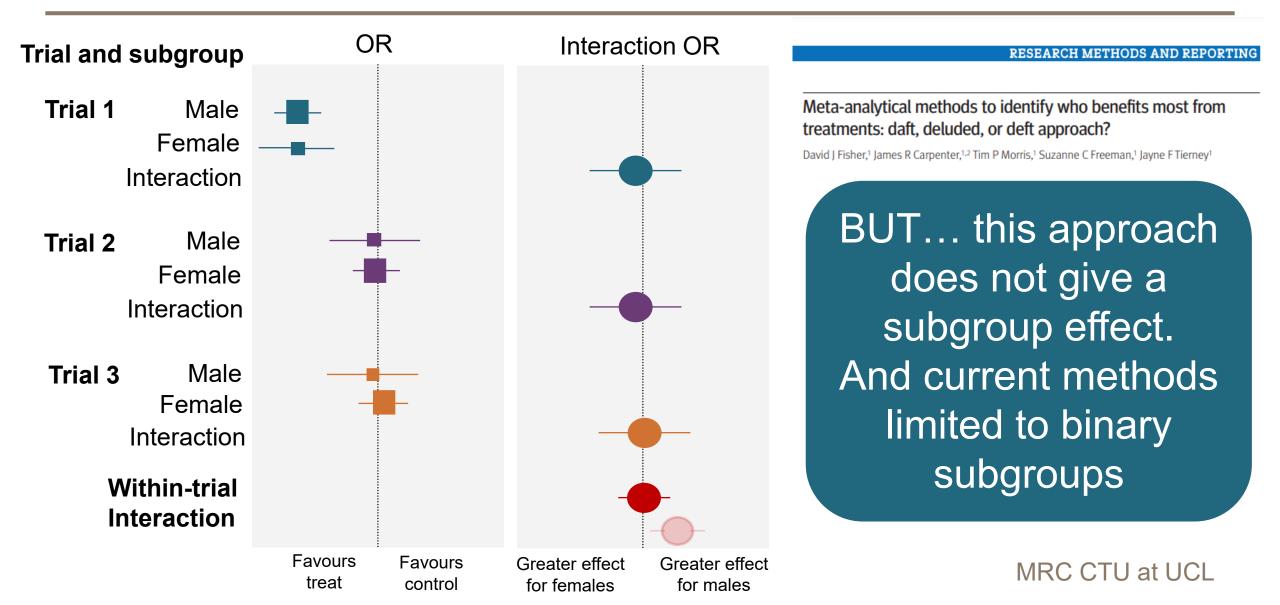
Treatment-covariate interactions



"Traditional" approach to treatment covariateinteractions (across- and within-trial)



Within-trial approach to treatment-covariate interactions



Within-trial framework: Aims



Reliably test for interactions between treatment and any categorical covariate



Estimate subgroup effects that are compatible with within-trial interactions



Ensure methodology is easy to use

Within-trial framework: Subgroup effects

- Meta-analysis with *n* trials (i = 1, ..., n)
- Covariate with k subgroups (j = 1, ..., k) Sex, k=2
- $\hat{\beta}_{ji}$ = observed trt. effect in subgroup *j* of trial *i*

 $\hat{\beta}_{11}$ is effect for males in trial 1 $\hat{\beta}_{21}$ is effect for females in trial 1

- $\hat{\beta}_i = vector$ of effects $\hat{\beta}_{ji}$ for trial *i*
- Standard MV-MA model:

$$\widehat{\boldsymbol{\beta}}_{1} = \begin{bmatrix} \widehat{\beta}_{11} \\ \widehat{\beta}_{21} \end{bmatrix} \quad \widehat{\boldsymbol{\beta}}_{2} = \begin{bmatrix} \widehat{\beta}_{12} \\ \widehat{\beta}_{22} \end{bmatrix} \quad \widehat{\boldsymbol{\beta}}_{n} = \begin{bmatrix} \widehat{\beta}_{1n} \\ \widehat{\beta}_{2n} \end{bmatrix}$$

$$\widehat{\boldsymbol{\beta}}_{i} \sim MVN(\boldsymbol{\beta}, \boldsymbol{S}_{i} + \boldsymbol{\Sigma}_{\boldsymbol{\beta}})$$
Subgroup effects in each trial ______ Between-trial heterogeneity matrix
Pooled subgroup effects _____ Covariance matrix

Within-trial framework: Interactions

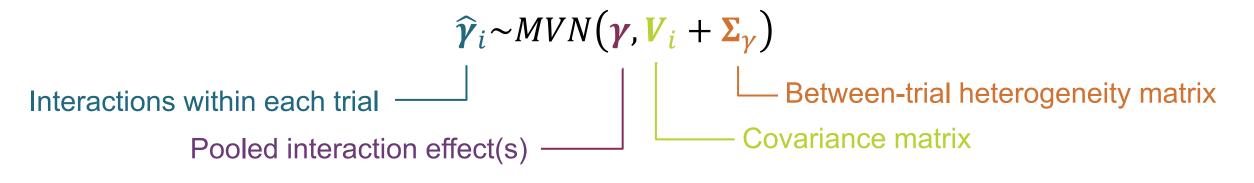
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$$\widehat{\boldsymbol{\gamma}}_{i} = \begin{bmatrix} \widehat{\gamma}_{2i} \\ \vdots \\ \widehat{\gamma}_{ki} \end{bmatrix} = \begin{bmatrix} \widehat{\beta}_{2i} - \widehat{\beta}_{1i} \\ \vdots \\ \widehat{\beta}_{ki} - \widehat{\beta}_{1i} \end{bmatrix}$$

k=2, so:
$$\hat{\boldsymbol{\gamma}}_i = \hat{\gamma}_{2i} = \hat{\beta}_{2i} - \hat{\beta}_{1i}$$

In each trial *i*, the within-trial interaction is:

[effect for females] – [effect for males]

• Standard MV-MA model:



Within-trial framework: Compatibility

- We wish to link the model for the subgroup effects (β) with the model for the interactions (γ)
- Define a **compatibility** relationship:

"Floating" subgroup effects $---\beta = \beta_1 \mathbf{1} + \begin{bmatrix} 0\\ \gamma \end{bmatrix}$

Pooled effect in reference subgroup —

 $\boldsymbol{\beta} = \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_1 + \gamma_2 \end{bmatrix}$

Subgroup effect for females is effect for males + interaction

——Pooled within-trial interaction(s)

- Vector of 1's, length k

• Relationship ensures that:

[difference between subgroup effects] = [within-trial interaction]

Within-trials framework: Step-by-step

- Step 1: Estimate the within-trial interaction γ and variance
- Step 2: Estimate "floating" subgroup effects (β) compatible with γ
- Step 3: Correct the "naïve" variance of β to account for the error in γ.

Example 1: Corticosteroid use in IL6 MA

- Setting: Patients hospitalised with COVID-19
- Studies: 15 RCTs
- Treatment: Tocilizumab
- Subgroup: Corticosteroid use at randomisation (Yes, No)
- Outcome: 28-day mortality (OR)

Research

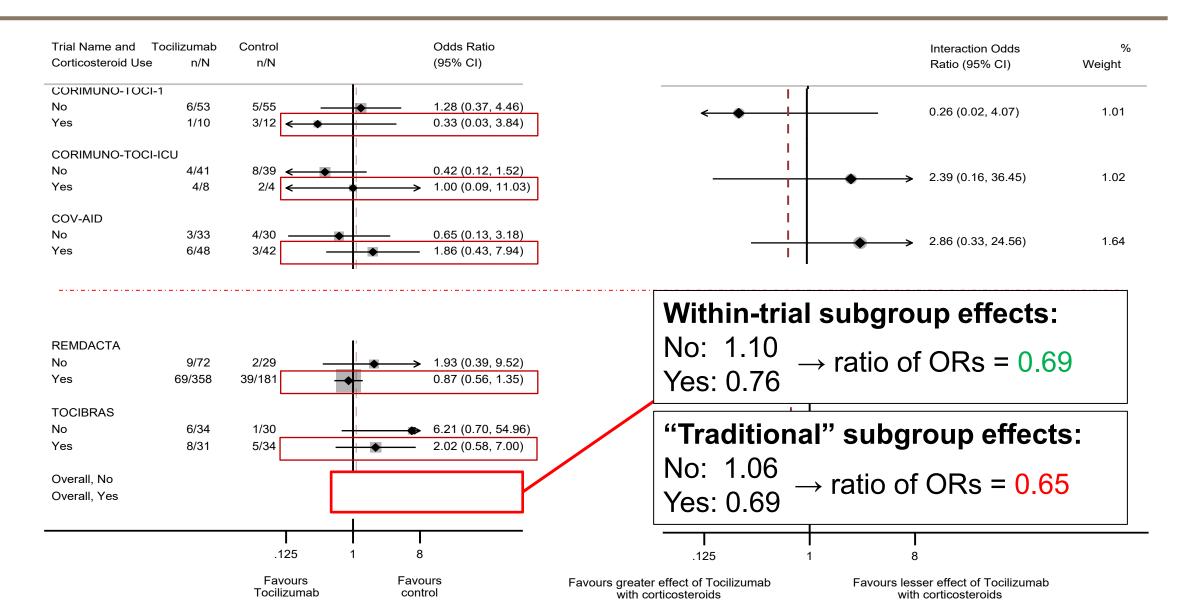
JAMA | Original Investigation

Association Between Administration of IL-6 Antagonists and Mortality Among Patients Hospitalized for COVID-19 A Meta-analysis

The WHO Rapid Evidence Appraisal for COVID-19 Therapies (REACT) Working Group



Example 1: Corticosteroid use in IL6 MA



Example 2: Nodal status in PORT MA

- Setting: Patients with non-small cell lung cancer
- Studies: 11 RCTs
- Treatment: Post operative radiotherapy (PORT)
- Subgroup: Nodal status (N0, N1, N2/3)
- Outcome: Overall survival (HR)

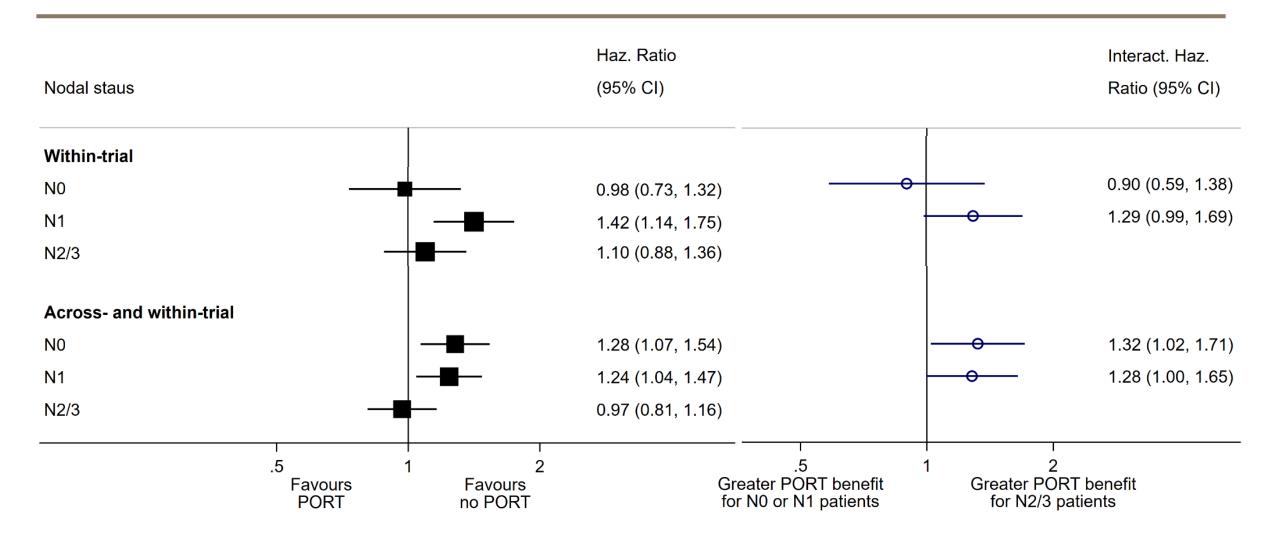


Postoperative radiotherapy for non-small cell lung cancer (Review)

Burdett S, Rydzewska L, Tierney J, Fisher D, Parmar MKB, Arriagada R, Pignon JP, Le Pechoux C, on behalf of the PORT Meta-analysis Trialists Group



Example 2: Nodal status in PORT MA



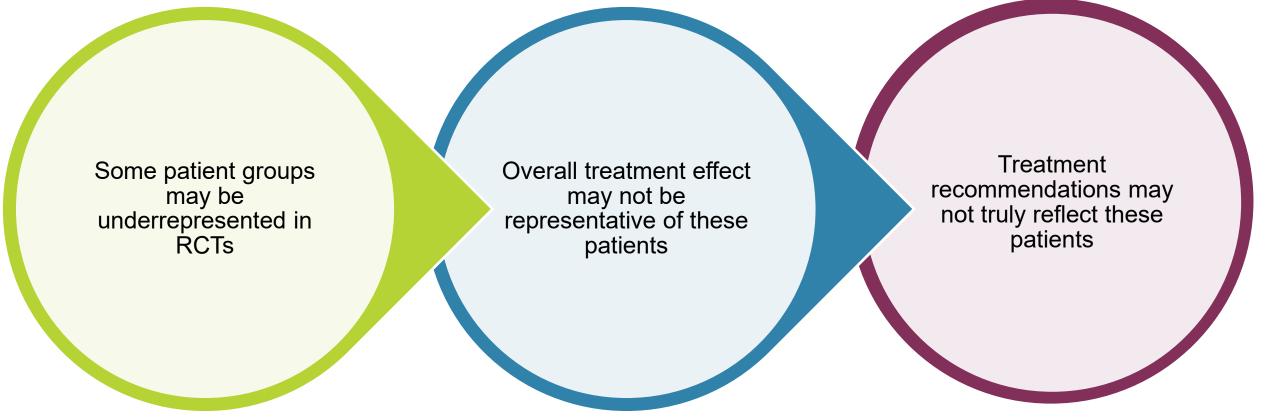
Summary, future work, and conclusion

Properties of the method	What's next?
 Designed for use with summary data or two-stage IPD Account for multiple sources of heterogeneity (subgroup effects and interactions) via random-effects 	 Paper under revision in Research Synthesis Methods Stata code available via GitHub (<u>https://github.com/ucl/metafloat</u>) Working on extension to IPD

Conclusion

• We present a complete meta-analytic framework for reliable estimation of how well treatments work for different groups of patients

How would you utilize equity, diversity, and inclusion in your methodology?



Meta-analysis using our within-trial framework may be the only way to get an appropriate estimate of the effect of treatment for these patient groups



• Peter Godolphin: No disclosures



References



Fisher D, et al. (Journal of Clinical Epidemiology, 2011), A critical review of methods for the assessment of patient-level interactions in individual patient data (IPD) meta-analysis of randomised trials, and guidance for practitioners
Fisher D, et al. (BMJ, 2017) Meta-analytical methods to identify who benefits most from treatments: daft, deluded, or deft approach?

Shankar-Hari M, et al. (JAMA, 2021) Association Between Administration of IL-6 Antagonists and Mortality Among Patients Hospitalized for COVID-19: A Meta-analysis

Burdett S, et al. (Cochrane Database of Systematic Reviews, 2016) *Postoperative radiotherapy for non-small cell lung cancer* MRC CTU at UCL

Incorporating heterogeneity into the framework

- Fully common effects: set Σ_{γ} and Σ_{β} to zero
- Partial random-effects model: Common-effect for the interactions $(\Sigma_{\gamma} = 0)$, random effects on the subgroup estimates
- Fully random-effects (common heterogeneity): Interactions and subgroups have (different) common heterogeneity parameters.
 Exchangeable structures for both Σ_γ and Σ_β
- Fully random-effects (unstructured): Allow unstructured heterogeneity covariances

Within-trials framework: the idea (k-level covariate)

- Using a k-subgroup covariate $\boldsymbol{\beta}_{i} = [\beta_{1i}, \beta_{2i}, \dots, \beta_{ki}]^{T}$, k > 2
- **Step 1:** Estimate the within-trial interaction (γ)

- Here
$$\boldsymbol{\gamma} = [\gamma_{2}, \gamma_{3}, \dots, \gamma_{k}]^{T}$$

– Work out the within-trial interactions (k-1 contrasts) for each study *i*:

$$\widehat{\boldsymbol{\gamma}}_{i} = \left[\widehat{\beta}_{2i} - \widehat{\beta}_{1i}, \dots, \widehat{\beta}_{ki} - \widehat{\beta}_{1i}\right]^{T}$$

- Pool $\hat{\gamma}_i$ to estimate γ in a MV-MA model

Within-trials framework: the idea (k-level covariate)

• Step 2: Estimate floating subgroup-specific treatment effects (β)

- Subtract γ from the non-reference subgroup values $(\hat{\beta}_{2i} \dots \hat{\beta}_{ki})$

- We then pool
$$\begin{bmatrix} \hat{\beta}_{1i} \\ \hat{\beta}_{2i} - \gamma_2 \\ \vdots \\ \hat{\beta}_{ki} - \gamma_k \end{bmatrix}$$
 in a MV-MA model to estimate θ

- Finally, we reverse our previous operations which scaled the non-

reference subgroup:
$$\hat{\boldsymbol{\beta}} = \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \vdots \\ \hat{\beta}_k \end{bmatrix} = \hat{\theta} \mathbf{1} + \begin{bmatrix} 0 \\ \hat{\boldsymbol{\gamma}} \end{bmatrix} = \begin{bmatrix} \hat{\theta} + 0 \\ \hat{\theta} + \hat{\gamma}_2 \\ \vdots \\ \hat{\theta} + \hat{\gamma}_k \end{bmatrix}$$

Example 2: Nodal status in PORT MA

