

# Extending Network Meta - Analysis to include Non - Randomized Evidence: Results of a scoping review



EVIDENCE  
SYNTHESIS  
METHODS  
STATISTICS TEAM



<sup>1</sup>Ourania Koutsouroumpa, <sup>1,2</sup>Katerina Maria Kontouli,  
<sup>1,3,4</sup>Sofia Tsokani, <sup>1</sup>Iro Ntaga, <sup>1,5</sup>Georgios Seitidis,  
<sup>1</sup>Dimitris Mavridis

<sup>1</sup>Department of Primary Education, University of Ioannina, Ioannina, Greece

<sup>2</sup>Faculty of Medicine, University of Thessaly

<sup>3</sup>School of Medicine, Aristotle University of Thessaloniki, Thessaloniki, Greece

<sup>4</sup>Methods Support Unit, Cochrane, UK

<sup>5</sup>Department of Psychology, University of Ioannina, Ioannina, Greece

✉ o.koutsouroumpa@uoi.gr

🌐 www.esm.uoi.gr



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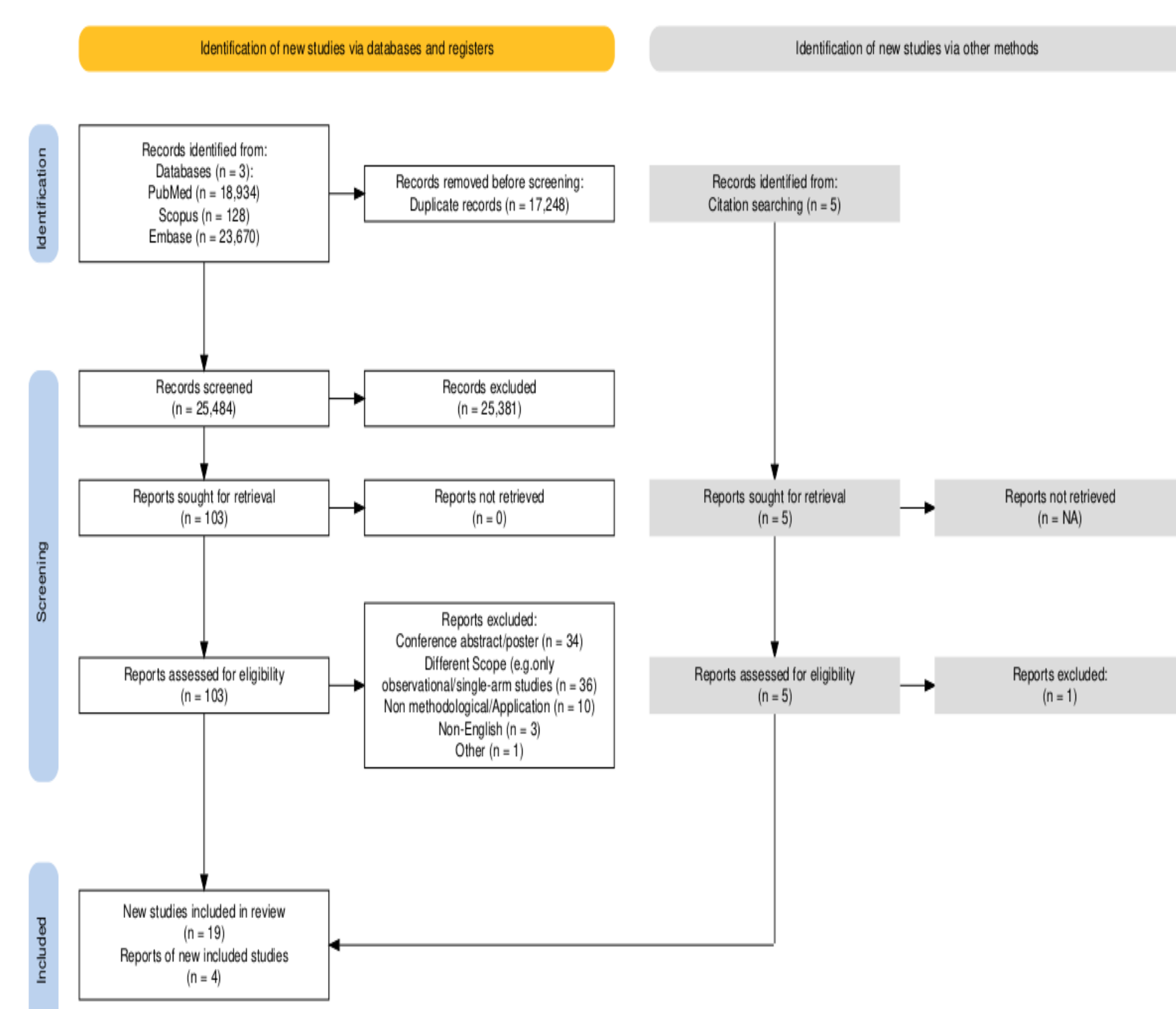
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## Background

Randomized clinical trials (RCTs) are considered the gold standard for evaluating the efficacy and safety of interventions and the synthesis of RCTs through meta-analysis (MA) is considered the strongest method for examining intervention effects. However, randomized evidence (RE) often suffer from low external validity, short follow-up time and limited feasibility. Non-randomized evidence (NRE), such as cohort studies and registries, can provide valuable insights as they may better reflect real-world conditions. We conducted a scoping review to identify the statistical methods used to combine RE and NRE within the MA or NMA frameworks.

## Flowchart

We searched Embase, PubMed, and Scopus up until June 2024. The following PRISMA flowchart summarizes the selection of studies for our review.



## Systematic Review finding

Of the 23 included studies, 17 were methodological papers focused on the integration of RE and NRE information in MA and NMA, while the remaining 6 were reviews of methods addressing the same topic. Among these 17 methodological studies:

- 11 (64.7%) focused on combining RE and NRE in standard MA
- 5 (29.4%) in NMA alone and
- 1 (5.9%) addressed both approaches

The majority - 15 studies (88.2%) - adopted a Bayesian framework. Regarding data types:

- 13 studies (76.4%) synthesized only aggregated data (AgD)
- 2 (11.8%) required individual participant data (IPD) and
- 2 (11.8%) incorporated both IPD and AgD

## Random-effects NMA model

- Within-study model

$$y_{i,jk} \sim \text{Normal}(\theta_{i,jk}, s_{i,jk}^2)$$

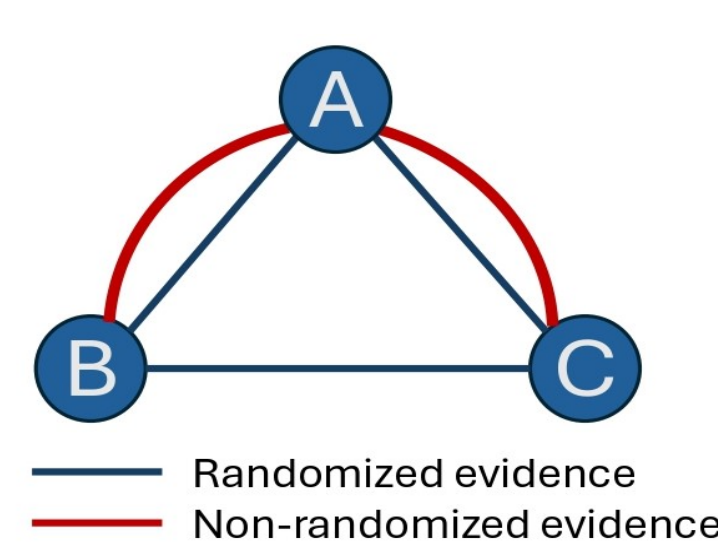
- Between-study model

$$\theta_{i,jk} \sim \text{Normal}(\mu_{jk}, \tau^2)$$

- Key assumptions:

✓ Exchangeability: Differences in observed effects are due to random variation or sampling error.

✓ Consistency: The direct and indirect evidence for a treatment comparison should agree.



## Identified methods

### → Naive data synthesis

All evidence (RCTs and NRE) is treated equally, without adjustment.

$$y_{i,jk} \sim \text{Normal}(\theta_{i,jk}, s_{i,jk}^2)$$

! No distinction between RCT and NRE, risk of bias (RoB) or design are not accounted for.

### → Design-adjusted analysis

Down-weights NRE by inflating their variance using a design-specific weight.

$$y_{i,jk} \sim \text{Normal}(\theta_{i,jk}, \frac{s_{i,jk}^2}{w_i})$$

Typically,  $w_{RCT} = 1, w_{NRE} < 1$

Can be set to fixed values or random variables.

✓ Accounts for uncertainty in NRE

✗ Subjective specification of down-weighting

### → Using NRE as prior information

- Predictive prior with down-weighted variance

This approach constructs a predictive distribution from NRE estimates and incorporates it a prior for  $\mu_{jk}$ , but downweights it by inflating the variance using a factor  $w_{jk}$

$$\mu_{jk} \sim \text{Normal}(\hat{\mu}_{jk}^{NRE} + \beta_{jk}, \frac{\hat{V}_{jk}^{NRE}}{w_{jk}})$$

- If  $\beta_{jk} = 0$  and  $w_{jk} = 1$  full trust in NRE
- If  $w_{jk} \ll 1$ , NRE evidence is heavily downweighted.
- ✓ Handles uncertainty and possible bias
- ✗ Requires specification of prior parameters and less useful with few NRS

- Power Prior

This method down-weights the contribution of NRE by raising its likelihood contribution to a power between  $a_i \in [0, 1]$

$$L(\mu|NRE) = \prod_{i=1}^k [L(\mu|NRE_i)]^{a_i}$$

✓ Flexible

✗ Choosing  $a_i$  values can be subjective

### → Three-level hierarchical model

First level, (within study differences)

$$y_{i,jk} \sim \text{Normal}(\theta_{i,jk}, s_{i,jk}^2)$$

Second level, (between study differences)

$$\theta_{i,jk} \sim \text{Normal}(\mu_{jk}^{design}, \tau^2)$$

Third level, (between design differences)

$$\mu_{jk}^{design} \sim \text{Normal}(\mu_{jk}, \tau_{design}^2)$$

✓ Accounts for design-specific effects and heterogeneity

✗ More complex, requires sufficient data per design

## References

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- [2] H. Hussein, K. R. Abrams, L. J. Gray, et al. Hierarchical network meta-analysis models for synthesis of evidence from randomised and non-randomised studies. *BMC Medical Research Methodology*, 23:97, 2023.



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