Addressing consistency in networks of randomized trials



Areti Angeliki Veroniki, MSc, PhD

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E-mail: VeronikiA@smh.ca

Knowledge Translation Program,

Li Ka Shing Knowledge Institute,

St. Michael's Hospital,

Toronto, Canada



St. Michael's





I have no actual or potential conflict of interest in relation to this presentation







Network Meta-analysis (NMA)

NMA has become increasingly popular over the last two decades with ~ 500 publications

- When policy makers are considering what interventions to cover through health plans or what safety labels to put on medications, they need evidence from an NMA because this method uses all available RCTs for a specific clinical topic
- The validity of the results from NMA rests on the assumption of transitivity, requiring that the pairwise comparisons are similar in factors which could affect the relative treatment effects.



Temporal distribution of publications (n=494)

*2015 sample is not complete



Transitivity assumption

The two sets of trials AC and CB do not differ with respect to the distribution of effect modifiers.

Age effect modifier





Transitivity assumption

Treatment C should be similar when it appears in AC and BC trials





Transitivity assumption







Consistency assumption

When the common comparator is transitive, it allows a valid indirect comparison of the treatments to which it is linked







Assumption underlying indirect comparison and NMA (in addition to considering homogeneity)



Cipriani et al Ann of Int Medicine 2013



Network Meta-analysis (NMA)

A database of 186 NMAs showed that...

In 24% of the networks the authors used inappropriate methods to evaluate consistency

- Comparison of direct with NMA estimates
- Comparison of previous meta-analyses with NMA results

In 44% of the networks the authors did not report a method to evaluate consistency









Consistency assumption





- What is the extent of inconsistency in complex networks?
- Which factors control its statistical significance?
- Which would be the most appropriate approach to employ?



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Evaluation of inconsistency in networks of interventions

Areti Angeliki Veroniki,¹ Haris S Vasiliadis,^{2,3} Julian PT Higgins^{4,5} and Georgia Salanti¹*

¹Department of Hygiene and Epidemiology, University of Ioannina School of Medicine, Ioannina, Greece, ²Department of Orthopaedics, School of Medicine, University of Ioannina, Greece, ³Molecular Cell Biology and Regenerative Medicine, Sahlgrenska Academy, University of Gothenburg, Sweden, ⁴MRC Biostatistics Unit, Cambridge, UK and ⁵Centre for Reviews and Dissemination, University of York, York, UK

*Corresponding author. Department of Hygiene and Epidemiology, University of Ioannina School of Medicine, University Campus, Ioannina 45110, Greece. E-mail: gsalanti@cc.uoi.gr

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Background The assumption of consistency, defined as agreement between direct and indirect sources of evidence, underlies the increasingly popular method of network meta-analysis. No evidence exists so far



<u>Aim</u>: To update our previous empirical evaluation by employing different statistical approaches to detect inconsistency and to estimate empirically the prevalence of inconsistency in a set of published networks.





Forms of Inconsistency

Loop Inconsistency





Forms of Inconsistency

Design Inconsistency





Approaches for evaluating...

LOCAL INCONSISTENCY

- Loop-Specific (LS)
- Node-splitting / Separating Indirect and Direct Evidence (SIDE)
- Separating One Design from the Rest (SODR)

GLOBAL INCONSISTENCY

- Composite test for inconsistency
- Lu and Ades (LA)
- Design by treatment interaction (DBT)
- Note: There is also Comparison of model fit and parsimony between consistency and inconsistency models approach
- Requires Bayesian framework uses the measures of model fit & parsimony (e.g. DIC)
- Does **not** provide inconsistency estimates
- Infers on global inconsistency





Fictional Dataset

studies	А	В	С	D	E	F
3						
2						
1						
1						
7						
6						
3						
1						
4						
1						
1						



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Loop-Specific (LS) Method

Multiple tests evaluating inconsistency within each closed <u>loop</u>





Loop-Specific (LS) Method

A

Multiple tests evaluating inconsistency within each closed <u>loop</u>

$$y_{i,AB} = \mu_{AB} + \delta_{i,AB} + \varepsilon_{i,AB}$$
$$y_{i,AC} = \mu_{AC} + \delta_{i,AC} + \varepsilon_{i,AC}$$
$$y_{i,BC} = \mu_{BC} + \delta_{i,BC} + \varepsilon_{i,BC}$$

$$IF_{ABC}^{LS} = |\mu_{AB} - (\mu_{AC} - \mu_{BC})|$$

<u>Statistical Evaluation</u>: $H_0: IF_{ABC}^{LS} = 0$

$$W_{LS} = \frac{\widehat{IF}_{ABC}^{LS}}{\sqrt{\widehat{Var}(IF_{ABC}^{LS})}} \sim N(0,1)$$
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Bucher et al. JCE 1997; Veroniki et al. Int J Epidemiol 2013



Node-Splitting or Separating Indirect and Direct Evidence (SIDE)

Multiple tests evaluating inconsistency for each <u>comparison</u> in the network





Node-Splitting or Separating Indirect and Direct Evidence (SIDE)





Design By Treatment Interaction (DBT) Model

<u>Global</u> Test assessing both <u>design</u> and <u>loop</u> inconsistency

A	В	С	D	E	F





Approaches for global inconsistency

Design By Treatment Interaction (DBT) Model

<u>Global</u> Test assessing both <u>design</u> and <u>loop</u> inconsistency





Approaches for global inconsistency

Lu and Ades (LA) model

<u>Global</u> test assessing <u>loop</u> inconsistency

$$y_{i,AB} = \mu_{AC} - \mu_{BC} + IF_{ABC} + \delta_{i,AB} + \varepsilon_{i,AB}$$

$$Statistical Evaluation: H_0: IF = 0$$

$$W^{LA} = IF'\Sigma^{-1}IF \sim \chi_f^2$$

$$He joint significance of all IFs is evaluated using the Global χ^2 test
$$Lu and Ades JASA 2006$$$$



Properties of the inconsistency approaches

	Loop- Specific	SIDE/ Node splitting	SODR	LA	DBT
Simple to compute	\checkmark	X	X	X	X
Insensitive to parameterization of multi-arm studies	X	X		X	
Indirect estimate derived from the entire network	X				
Does not suffer from multiple testing	X	X	X		
Power	X	X	?	X	?

Song et al BMC Med Res Methodol 2012, Veroniki et al BMC Med Res Methodol 2014



Database with 40 networks of interventions

Loop-Specific (LS) Method

- Out of the 303 loops :
- ☑ The loop inconsistency rate ranges between 2% and 10%
- Statistical inconsistency does **not** importantly differ between the four *effect measures*:

	OR	RRH	RRB	RD
Within-loop heterogeneity	8%	9%	10%	10%
Within-network heterogeneity	5%	6%	6%	5%



Database with 40 networks of interventions

Loop-Specific (LS) Method

☑ The different assumptions and estimators for heterogeneity can importantly **impact** on the assessment of inconsistency:

	OR	RRH	RRB	RD
Within-loop heterogeneity	8%	9%	10%	10%
Within-network heterogeneity	5%	6%	6%	5%

	DL	REML	SJ
Within-loop heterogeneity	8%	7%	5%

- Evidence loops that include comparisons informed by a single study are more likely to show inconsistency:
 - 2% to 9% depending on the estimator and assumption for heterogeneity



Distribution of IF in loops

Loop-Specific (LS) Method





Inference on networks

Design by treatment interaction (DBT) model



The *consistency* models display <u>higher</u> heterogeneity accounting probably for *inconsistency* in the data



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Veroniki et *al* IJE 2013



In summary...

- Inconsistency can occur in one in ten of the loops and in one in eight of the networks.
- Lower statistical heterogeneity is associated with more chances to detect inconsistency but the estimated magnitude of inconsistency is lower
- □ Care is needed when interpreting the results of a consistency test as issues of heterogeneity and power may limit its usefulness
- Results and inferences on the prevalence of inconsistency are sensitive to the estimation method of the heterogeneity.
- A sensitivity analysis in the assumptions of heterogeneity may be needed before concluding the absence of statistical inconsistency, particularly in networks with few studies.



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