



AGENCY FOR HEALTHCARE RESEARCH AND QUALITY



Quantitative Synthesis

Learning Objectives and Recommendations

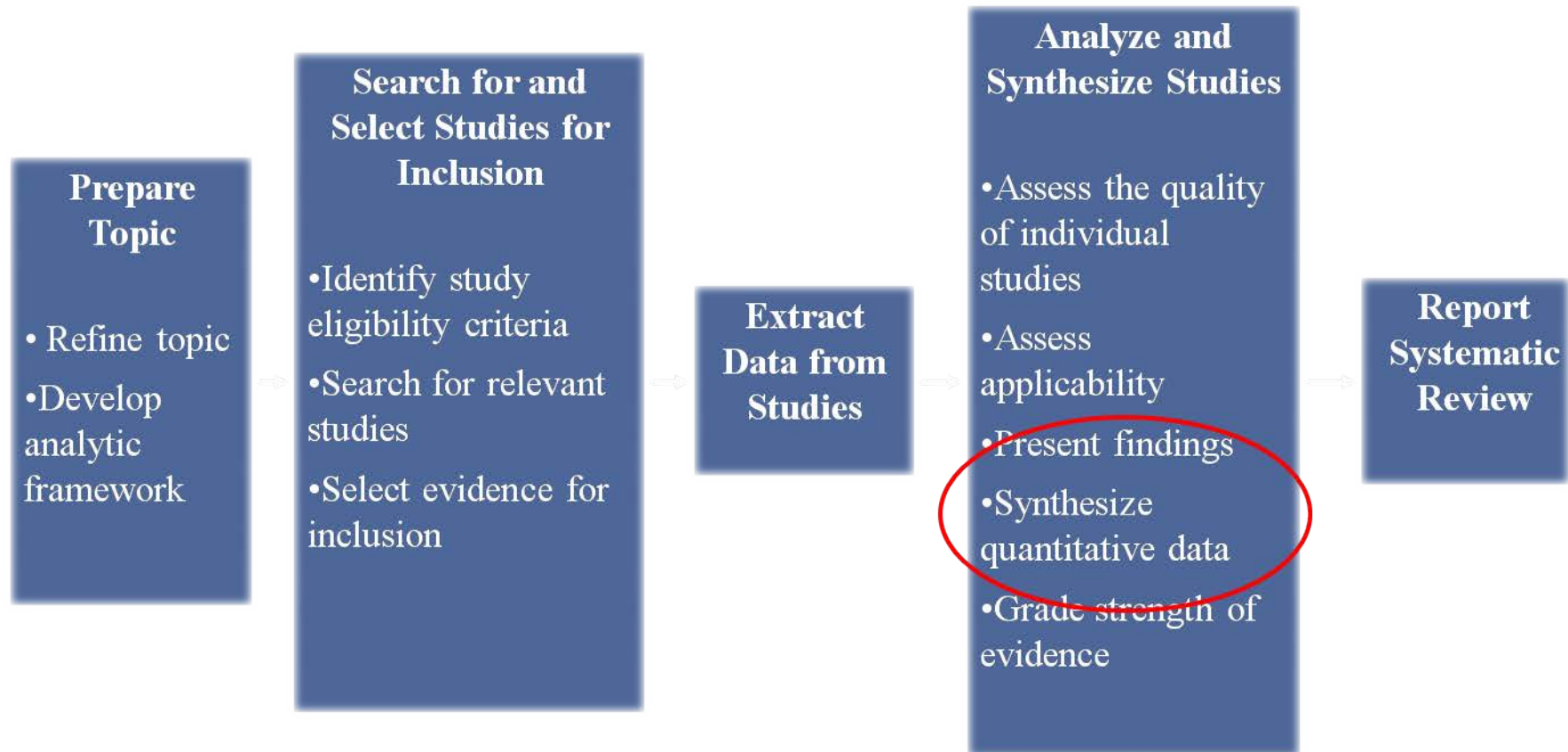
Background

- Purpose:
 - ▶ To consolidate and update guidance from prior methods guides
 - ▶ Focuses on ***Comparative Effectiveness Reviews (CERs)***:
 - Systematic reviews comparing effectiveness and harms of alternative clinical options
 - Help clinicians, policy-makers, patients make informed treatment choices
 - ▶ Focuses on interventional studies, not diagnostic, individual-level, or observational studies

Background

- Quantitative synthesis (meta-analysis) is a critical component of CERs.
- Quantitative synthesis should be conducted transparently, consistently, with methodology explicitly reported.
- This guide supports this process, but is not a comprehensive review or a text.
- Addresses the issues commonly encountered conducting CERs, in the order they occur.
- More details on individual chapters can be found here: [\[Link\]](#)

Systematic review process overview



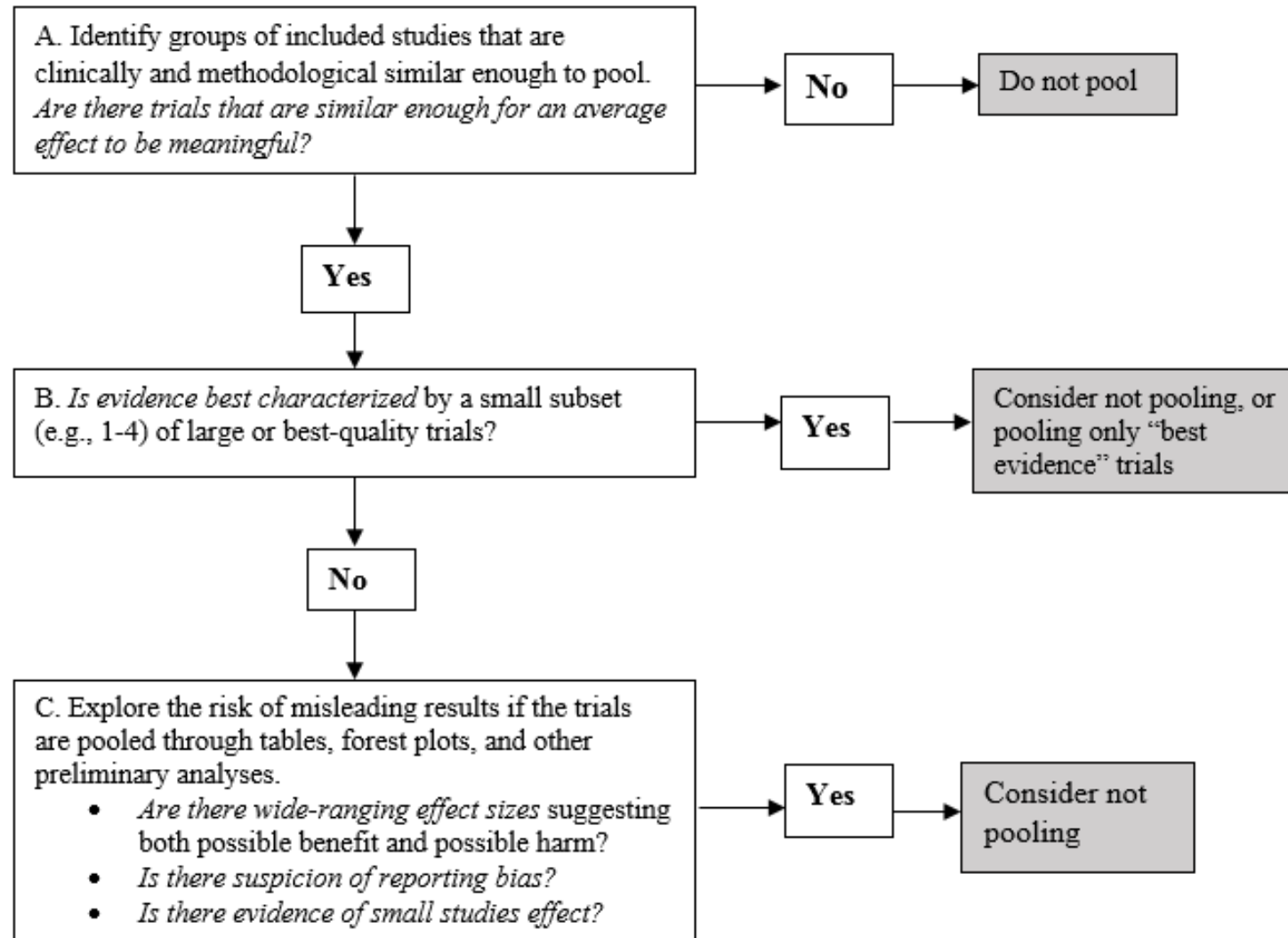
Learning objectives

- **Chapter 1:** Be able to describe the basic principles of combining data and when this is appropriate.
- **Chapter 2:** Be able to recognize common measures of association for meta-analysis (e.g., risk difference, odds ratio).
- **Chapter 3:**
 - ▶ 1. Be able to describe a scenario for which a fixed effects versus random effects model may be appropriate.
 - ▶ 2. Be able to list different types of estimators for random effects models.
 - ▶ 3. Be able to describe the strengths and weaknesses for each of the estimators for different types of data.
- **Chapter 4:** Be able to distinguish between (1) clinical and methodological heterogeneity, and (2) statistical heterogeneity.
- **Chapter 5:** Be able to understand the network meta-analysis approach and when it can be implemented

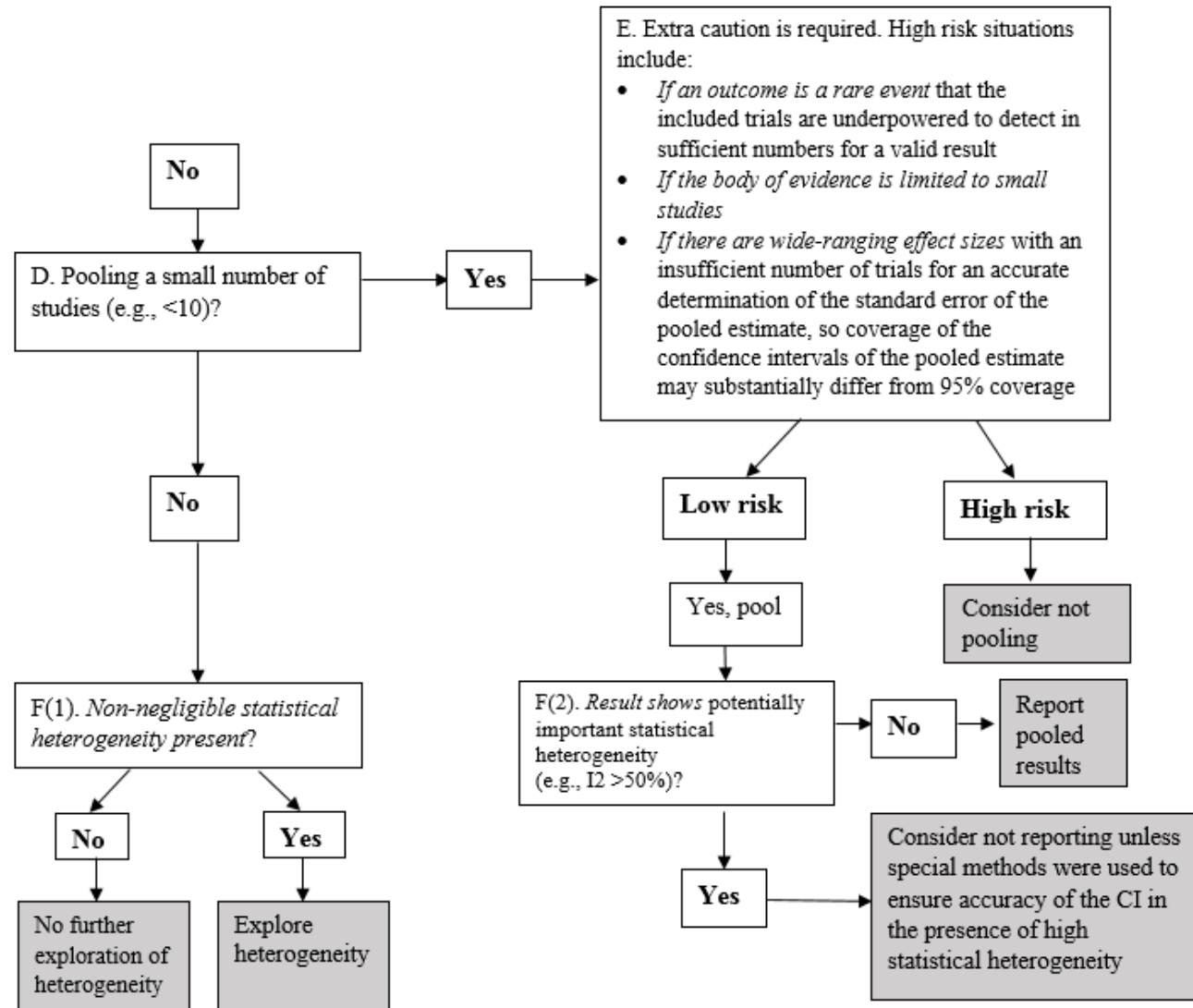
Recommendation for Chapter 1: Decision to combine trials

- Use the pooling decision tree on subsequent slides when deciding whether to combine data.

Pooling Decision Tree (1)



Pooling Decision Tree (2)



Recommendations for

Chapter 2. Different effects for different data types

- **For binary outcomes:**
 - ▶ Consider carefully which binary measure to analyze.
 - ▶ Risk difference is the preferred measure if conversion to NNT or NNH is sought.
 - ▶ Risk ratio and odds ratio are likely to be more consistent than the risk difference when studies differ in baseline risk.
 - ▶ Risk difference is not the preferred measure when the event is rare.
 - ▶ Risk ratio is not the preferred measure if switching between occurrence and non-occurrence of the event is important to the meta-analysis.
 - ▶ The odds ratio can be misleading.
- **For continuous outcomes:**
 - ▶ When studies use the same metric, mean difference is preferred measure.
 - ▶ When calculating standardized mean difference, Hedges' g is preferred over Cohen's d due to the reduction in bias.
- **General:**
 - ▶ If baseline values are unbalanced, perform an ANCOVA analysis. If ANCOVA cannot be performed and the correlation is greater than 0.5, change from baseline values should be used to compute the mean difference.
 - If the correlation is less than or equal to 0.5, follow-up values should be used.
 - ▶ Data from clustered randomized trials should be adjusted for the design effect.

Recommendations for

Chapter 3. Statistical models for meta-analysis

- PL method appears to generally perform best. The DL method is also appropriate when between-study heterogeneity is low.
- **For study-level aggregated binary data and count data**, use of a generalized linear mixed effects model assuming random treatment effects is also recommended.
- **For rare binary events:**
 - ▶ Avoid methods that use continuity corrections.
 - ▶ For studies with zero events in one arm, or studies with sparse binary data but no zero events, obtain an estimate using the Peto method, the Mantel-Haenszel method, or a logistic regression approach, without adding a correction factor, when the between-study heterogeneity is low.
 - ▶ When the between-study heterogeneity is high, and/or there are studies with zero events in both arms, more recently developed methods such as a beta-binomial model could be explored and used.
 - ▶ Conduct sensitivity analyses with acknowledgement of the inadequacy of data.
- If choosing Bayesian methods, use of vague priors is supported.

Recommendations for

Chapter 4. Statistical heterogeneity

- Expect, visually inspect, quantify, and sufficiently address statistical heterogeneity in all meta-analyses.
- Include prediction intervals in all forest plots.
- Consider evaluating multiple metrics of heterogeneity, between-study variance, and inconsistency (i.e., Q , τ^2 and I^2 along with their respective confidence intervals when possible).
- A non-significant Q should not be interpreted as the absence of heterogeneity, and there are nuances to the interpretation of Q that carry over to the interpretation of τ^2 and I^2 .
- Random effects is the preferred method for meta-regression that should be used under consideration of low power associated with limited studies (i.e., <10 studies per study-level factor) and the potential for ecological bias.
- A simplified two-step approach to control-rate meta-regression that involves scatter plotting and then hierarchical or Bayesian meta-regression is recommended.
- Routine use of multivariate meta-analysis not recommended.

Recommendations for Chapter 5. Network meta-analysis

- Always base a network meta-analysis on a rigorous systematic review.
- **For a network meta-analysis, three assumptions must be met :**
 - ▶ Homogeneity of direct evidence
 - ▶ Transitivity, similarity, or exchangeability
 - ▶ Consistency (between direct and indirect evidence)
- Investigators may choose a frequentist or Bayesian mode of inference based on the research team's expertise, complexity of evidence network, and the research question.
- **Evaluating inconsistency** is a major and mandatory component of network meta-analysis.
 - ▶ Conducting a global test should not be the only method used to evaluate inconsistency. A loop-based approach can identify the comparisons that cause inconsistency.
- **Cautiously use inference based on the rankings and probabilities of treatments being most effective.**
 - ▶ Rankings and probabilities can be misleading and should be interpreted based on the magnitude of pairwise effect sizes. Despite such rankings, differences across interventions may not be clinically important.

Resources for Chapter 1



1. Chou R, Aronson N, Atkins D, et al. AHRQ series paper 4: assessing harms when comparing medical interventions: AHRQ and the effective health-care program. *J Clin Epidemiol*. 2010;63(5):502-12. PMID:18823754 <http://dx.doi.org/10.1016/j.jclinepi.2008.06.007>
2. Verbeek J, Ruotsalainen J, Hoving JL. Synthesizing study results in a systematic review. *Scand J Work Environ Health*. 2012;38(3):282-90. <http://dx.doi.org/10.5271/sjweh.3201>
3. Berlin JA, Crowe BJ, Whalen E, et al. Meta-analysis of clinical trial safety data in a drug development program: Answers to frequently asked questions. *Clin Trials*. 2013;10(1):20-31. <http://dx.doi.org/10.1177/1740774512465495>
4. Gagnier JJ, Morgenstern H, Altman DG, et al. Consensus-based recommendations for investigating clinical heterogeneity in systematic reviews. *BMC Med Res Methodol*. 2013;13(1):106. <http://dx.doi.org/10.1186/1471-2288-13-106>
5. Thomas J, Askie LM, Berlin JA, Elliott JH, Ghera D, Simmonds M, Takwoingi Y, Tierney JF, Higgins JPT. Chapter 22: Prospective approaches to accumulating evidence. In: Higgins JPT, Thomas J, Chandler J, Cumpston M, Li T, Page MJ, Welch VA (editors). *Cochrane Handbook for Systematic Reviews of Interventions* version 6.0 (updated July 2019). Cochrane, 2019. Available from www.training.cochrane.org/handbook.
6. Schmid CH. Outcome reporting bias: a pervasive problem in published meta-analyses. *American Journal of Kidney Diseases*. 2016;69(2):172-4.
7. Bowater RJ, Escarola G. Heterogeneity and study size in random-effects meta-analysis. *J Appl Stat* 2013;40(1):2-16. <https://doi.org/10.1080/02664763.2012.700448>
8. Turner RM, Bird SM, Higgins JP. The Impact of Study Size on Meta-analyses: Examination of Underpowered Studies in Cochrane Reviews. *PloS One*. 2013;8(3):e59202. <http://dx.doi.org/10.1371/journal.pone.0059202>
9. Kontopantelis E, Reeves D. Performance of statistical methods for meta-analysis when true study effects are non-normally distributed: A simulation study. *Stat Methods Med Res*. 2012;21(4):409-26. <http://dx.doi.org/10.1177/0962280210392008>
10. Deeks JJ, Higgins JPT, Altman DG (editors). Chapter 10: Analysing data and undertaking meta-analyses. In: Higgins JPT, Thomas J, Chandler J, Cumpston M, Li T, Page MJ, Welch VA (editors). *Cochrane Handbook for Systematic Reviews of Interventions* version 6.0 (updated July 2019). Cochrane, 2019. Available from www.training.cochrane.org/handbook.

Resources for Chapter 2



1. Moher D, Liberati A, Tetzlaff J, et al. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. PLoS Med. 2009;6(7):e1000097. PMID: 19621072 <http://dx.doi.org/10.1371/journal.pmed.1000097>
2. Schulzer M, Mancini GJ. 'Unqualified Success' and 'Unmitigated Failure' Number-Needed-to-Treat-Related Concepts for Assessing Treatment Efficacy in the Presence of Treatment-Induced Adverse Events. Int J Epidemiol. 1996;25(4):704-12.
3. Altman DG. Confidence intervals for the number needed to treat. BMJ. 1998;317(7168):1309. PMID: 9804726
4. Newcombe RG. Interval estimation for the difference between independent proportions: comparison of eleven methods. Stat Med 1998;17(8):873-90. PMID: 9595617.
5. Fu R, Vandermeer BW, Shamliyan TA, et al. Handling Continuous Outcomes in Quantitative Synthesis Agency for Healthcare Research and Quality. Rockville, MD: 2013.

Resources for Chapter 3



1. DerSimonian R, Laird N. Meta-analysis in clinical trials. *Control Clin Trials*. 1986;7(3):177-88.
[https://doi.org/10.1016/0197-2456\(86\)90046-2](https://doi.org/10.1016/0197-2456(86)90046-2)
2. Brockhaus AC, Bender R, Skipka G. The Peto odds ratio viewed as a new effect measure. *Stat Med*. 2014;33(28):4861-74. <http://dx.doi.org/10.1002/sim.6301>
3. Hartung J, Knapp G. On tests of the overall treatment effect in meta-analysis with normally distributed responses. *Stat Med* 2001;20(12):1771-82. PMID: 11406840. <http://dx.doi.org/10.1002/sim.79164>
4. Hartung J, Knapp G. A refined method for the meta-analysis of controlled clinical trials with binary outcome. *Stat Med* 2001;20(24):3875-89. PMID: 11782040
5. Sidik K, Jonkman JN. A simple confidence interval for meta-analysis. *Stat Med*. 2002;21(21):3153-9.
6. Brockwell SE, Gordon IR. A comparison of statistical methods for meta-analysis. *Stat Med* 2001;20(6):825-40. PMID: 11252006. <http://dx.doi.org/10.1002/sim.650>
7. Bradburn MJ, Deeks JJ, Berlin JA, et al. Much ado about nothing: a comparison of the performance of meta-analytical methods with rare events. *Stat Med* 2007;26(1):53-77. PMID: 16596572. <http://dx.doi.org/10.1002/sim.2528>
8. Shuster JJ, Walker MA. Low-event-rate meta-analyses of clinical trials: implementing good practices. *Stat Med*. 2016. <http://dx.doi.org/10.1002/sim.6844>
9. Fleiss J. The statistical basis of meta-analysis. *Stat Methods Med Res*. 1993;2(2):121-45. PMID: 8261254. <http://dx.doi.org/10.1177/09622802930020020272>.
10. Vandermeer B, Bialy L, Hooton N, et al. Meta-analyses of safety data: a comparison of exact versus asymptotic methods. *Stat Methods Med Res*. 2009;18(4):421-32. <http://dx.doi.org/10.1177/0962280208092559>
11. Kuss O. Statistical methods for metaanalyses including information from studies without any events-add nothing to nothing and succeed nevertheless. *Stat Med*. 2015;34(7):1097-116. <http://dx.doi.org/10.1002/sim.6383>
12. Dias S, Sutton AJ, Ades AE, et al. Evidence Synthesis for Decision Making 2: A Generalized Linear Modeling Framework for Pairwise and Network Meta-analysis of Randomized Controlled Trials. *Med Decis Making*. 2013;33(5):607-17. <http://dx.doi.org/10.1177/0272989X12458724>
13. Lambert PC, Sutton AJ, Burton PR, et al. How vague is vague? A simulation study of the impact of the use of vague prior distributions in MCMC using WinBUGS. *Stat Med*. 2005;24(15):2401-28. PMID: 16015676. <http://dx.doi.org/10.1002/sim.2112>

Resources for Chapter 4



1. Sterne JA, Sutton AJ, Ioannidis JP, et al. Recommendations for examining and interpreting funnel plot asymmetry in meta-analyses of randomised controlled trials. *BMJ*. 2011;343:d4002. <http://dx.doi.org/10.1136/bmj.d4002> 114.
2. Langan D, Higgins JP, Simmonds M. An empirical comparison of heterogeneity variance estimators in 12,894 meta-analyses. *Res Synth Methods*. 2015;6(2):195-205. <http://dx.doi.org/10.1002/jrsm.1140>
3. Higgins JP. Commentary: Heterogeneity in meta-analysis should be expected and appropriately quantified. *Int J Epidemiol*. 2008;37(5):1158-60. <https://doi.org/10.1093/ije/dyn204>
4. Anzueto-Cabrera J, Higgins JPT. Graphical displays for meta-analysis: An overview with suggestions for practice. *Res Synth Methods*. 2010;1(1):66-80. <http://dx.doi.org/10.1002/jrsm.6>
5. [Forest plot example taken from] Barrington KJ. Umbilical artery catheters in the newborn: effects of position of the catheter tip. *Cochrane Database Syst Rev* 2000;(2):CD000505. <http://dx.doi.org/10.1002/14651858.CD000505>
6. [Forest plot example reprinted from] Pakos E, et al. Patellar resurfacing in total knee arthroplasty. A meta-analysis. *Bone Joint Surg Am* 2005;87:1438-45 [10.2106/JBJS.D.02422](http://dx.doi.org/10.2106/JBJS.D.02422), with permission from Rockwater, Inc.
7. Int'Hout J, Ioannidis JP, Rovers MM, et al. Plea for routinely presenting prediction intervals in meta-analysis. *BMJ Open*. 2016;6(7):e010247. PMID: 27406637. <http://dx.doi.org/10.1136/bmjopen-2015-010247>
8. Terrin N, Schmid CH, Lau J. In an empirical evaluation of the funnel plot, researchers could not visually identify publication bias. *J Clin Epidemiol*. 2005;58(9):894-901. <https://doi.org/10.1016/j.jclinepi.2005.01.006>
9. Egger M, Smith GD, Schneider M, et al. Bias in meta-analysis detected by a simple, graphical test. *BMJ*. 1997;315(7109):629-34. PMID: 9310563.
10. Higgins JP, Thompson SG, Deeks JJ, et al. Measuring inconsistency in meta-analyses. *BMJ*. 2003;327(7414):557-60. PMID: 12958120. <http://dx.doi.org/10.1136/bmj.327.7414.557>
11. DerSimonian R, Laird N. Meta-analysis in clinical trials. *Control Clin Trials*. 1986;7(3):177-88. [https://doi.org/10.1016/0197-2456\(86\)90046-2](https://doi.org/10.1016/0197-2456(86)90046-2)
12. Veroniki AA, Jackson D, Viechtbauer W, et al. Methods to estimate the between-study variance and its uncertainty in meta-analysis. *Res Synth Methods*. 2016;7(1):55-79. <http://dx.doi.org/10.1002/jrsm.1164>
13. Hoaglin DC. Misunderstandings about Q and 'Cochran's Q test' in meta-analysis. *Stat Med*. 2016;35(4):485-95. <http://dx.doi.org/10.1002/sim.6632>
14. Deeks JJ, Higgins JPT, Altman DG (editors). Chapter 10: Analysing data and undertaking meta-analyses. In: Higgins JPT, Thomas J, Chandler J, Cumpston M, Li T, Page MJ, Welch VA (editors). *Cochrane Handbook for Systematic Reviews of Interventions* version 6.0 (updated July 2019). Cochrane, 2019. Available from www.training.cochrane.org/handbook.
15. Thompson SG, Higgins J. How should meta-regression analyses be undertaken and interpreted? *Stat Med*. 2002;21(11):1559-73. <http://dx.doi.org/10.1002/sim.1187>
16. Berkey CS, Hoaglin DC, Mosteller F, et al. A random-effects regression model for meta-analysis. *Stat Med* 1995;14(4):395-411. PMID: 7746979
17. Knapp G, Hartung J. Improved tests for a random effects meta-regression with a single covariate. *Stat Med* 2003;22(17):2693-710. <http://dx.doi.org/10.1002/sim.1482>
18. Gagnier JJ, Morgenstern H, Altman DG, et al. Consensus-based recommendations for investigating clinical heterogeneity in systematic reviews. *BMC Med Res Methodol*. 2013;13(1):106. <http://dx.doi.org/10.1186/1471-2288-13-106>
19. Berlin JA, Santanna J, Schmid CH, et al. Individual patient-versus group-level data meta-regressions for the investigation of treatment effect modifiers: ecological bias rears its ugly head. *Stat Med*. 2002;21(3):371-87. <http://dx.doi.org/10.1002/sim.1023>
20. Borenstein M, Higgins JPT. Meta-Analysis and Subgroups. *Prev Sci*. 2013;14(2):134-43. <http://dx.doi.org/10.1007/s11121-013-0377-7>
21. Lau J, Antman EM, Jimenez-Silva J, et al. Cumulative meta-analysis of therapeutic trials for myocardial infarction. *N Engl J Med*. 1992;327(4):248-54. <http://dx.doi.org/10.1056/NEJM199207233270406>
22. M.W. M. The population risk as an explanatory variable in research synthesis of clinical trials. *Stat Med*. 1996;15(16):1713-28. [http://dx.doi.org/10.1002/\(SICI\)10970258\(19960830\)15:163.O.CO;2-D144](http://dx.doi.org/10.1002/(SICI)10970258(19960830)15:163.O.CO;2-D144)
23. Schmid CH, Lau J, McIntosh MW, et al. An empirical study of the effect of the control rate as a predictor of treatment efficacy in meta-analysis of clinical trials. *Stat Med*. 1998;17(17):1923-42.

Resources for Chapter 5



1. Guyatt GH, Oxman AD, Kunz R, et al. GRADE guidelines: 7. Rating the quality of evidence—inconsistency. *J Clin Epidemiol.* 2011;64(12):1294-302. PMID: 21803546. <http://dx.doi.org/10.1016/j.jclinepi.2011.03.017>
2. Mills EJ, Ioannidis JP, Thorlund K, et al. How to use an article reporting a multiple treatment comparison meta-analysis. *JAMA* 2012;308(12):1246-53. PMID: 23011714. <http://dx.doi.org/10.1001/2012.jama.11228>
3. Higgins JPT, Jackson D, Barrett JK, et al. Consistency and inconsistency in network meta-analysis: concepts and models for multi-arm studies. *Res Synth Methods.* 2012;3(2):98-110. <http://dx.doi.org/10.1002/jrsm.1044> 172.
4. Salanti G. Indirect and mixed-treatment comparison, network, or multiple-treatments meta-analysis: many names, many benefits, many concerns for the next generation evidence synthesis tool. *Res Synth Methods.* 2012;3(2):80-97. <http://dx.doi.org/10.1002/jrsm.1037>
5. Bucher HC, Guyatt GH, Griffith LE, et al. The results of direct and indirect treatment comparisons in meta-analysis of randomized controlled trials. *J Clin Epidemiol.* 1997;50(6):683-91. PMID: 9250266
6. Glenny A, Altman D, Song F, et al. Indirect comparisons of competing interventions. *Health Technol Assess* 2005; PMID: 16014203
7. Lumley T. Network meta-analysis for indirect treatment comparisons. *Stat Med.* 2002;21(16):2313-24. PMID: 12210616. <http://dx.doi.org/10.1002/sim.1201>
8. Salanti G, Higgins JP, Ades A, et al. Evaluation of networks of randomized trials. *Stat Methods Med Res.* 2008;17(3):279-301. PMID: 17925316. <http://dx.doi.org/10.1177/0962280207080643>
9. White IR, Barrett JK, Jackson D, et al. Consistency and inconsistency in network meta-analysis: model estimation using multivariate meta-regression. *Res Synth Methods.* 2012;3(2):111-25. <http://dx.doi.org/10.1002/jrsm.1045>
10. Lu G, Ades A. Assessing Evidence Inconsistency in Mixed Treatment Comparisons *J Am Stat Assoc.* 2006;101(20):447-59 <https://doi.org/10.1198/01621450500000130> 2
11. van der Valk R, Webers CAB, Lumley T, et al. A network meta-analysis combined direct and indirect comparisons between glaucoma drugs to rank effectiveness in lowering intraocular pressure. *J Clin Epidemiol.* 2009;62(12):1279-83. <http://dx.doi.org/10.1016/j.jclinepi.2008.04.012>
12. Dias S, Welton NJ, Caldwell DM, et al. Checking consistency in mixed treatment comparison meta-analysis. *Stat Med.* 2010;29(7-8):932-44. <http://dx.doi.org/10.1002/sim.3767>
13. Puhan MA, Schünemann HJ, Murad MH, et al. A GRADE Working Group approach for rating the quality of treatment effect estimates from network meta-analysis. *BMJ.* 2014;349:g5630. PMID: 26085374. <http://dx.doi.org/10.1136/bmj.h3326>
14. Salanti G, Ades AE, Ioannidis JP. Graphical methods and numerical summaries for presenting results from multiple-treatment meta-analysis: an overview and tutorial. *J Clin Epidemiol.* 2011;64(2):163-71. <http://dx.doi.org/10.1016/j.jclinepi.2010.03.016>
15. Murad MH, Montori VM, Ioannidis JP, et al. How to read a systematic review and meta-analysis and apply the results to patient care: users' guides to the medical literature. *JAMA.* 2014;312(2):171-9. PMID: 25005654. <http://dx.doi.org/10.1001/jama.2014.555916>
16. Bafeta A, Trinquart L, Seror R, et al. Reporting of results from network meta-analyses: methodological systematic review. *BMJ.* 2014;348; PMID: 24618053. <http://dx.doi.org/10.1136/bmj.g1741>. 215.
17. Song F, Loke YK, Walsh T, et al. Methodological problems in the use of indirect comparisons for evaluating healthcare interventions: survey of published systematic reviews. *BMJ.* 2009;338:b1147.216
18. Hutton B, Salanti G, Chaimani A, et al. The quality of reporting methods and results in network meta-analyses: an overview of reviews and suggestions for improvement. *PloS One.* 2014;9(3):e92508. <http://dx.doi.org/10.1371/journal.pone.0092508>
19. Moher D, Liberati A, Tetzlaff J, et al. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *PLoS Med.* 2009;6(7):e1000097. PMID: 19621072 <http://dx.doi.org/10.1371/journal.pmed.1000097>