



GRADE guidelines 17

DOI:

[10.1016/j.jclinepi.2017.05.005](https://doi.org/10.1016/j.jclinepi.2017.05.005)

Document Version

Accepted author manuscript

[Link to publication record in Manchester Research Explorer](#)

Citation for published version (APA):

Guyatt, G. H., Ebrahim, S., Alonso-Coello, P., Johnston, B. C., Mathioudakis, A. G., Briel, M., Mustafa, R. A., Sun, X., Walter, S. D., Heels-Ansdell, D., Neumann, I., Kahale, L. A., Iorio, A., Meerpohl, J., Schünemann, H. J., & Akl, E. A. (2017). GRADE guidelines 17: Assessing the risk of bias associated with missing participant outcome data in a body of evidence. *Journal of Clinical Epidemiology*. <https://doi.org/10.1016/j.jclinepi.2017.05.005>

Published in:

Journal of Clinical Epidemiology

Citing this paper

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Accepted Manuscript

GRADE guidelines 17: Assessing the Risk of Bias Associated with Missing Participant Outcome Data in a body of evidence

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PII: S0895-4356(16)30811-3

DOI: [10.1016/j.jclinepi.2017.05.005](https://doi.org/10.1016/j.jclinepi.2017.05.005)

Reference: JCE 9399

To appear in: *Journal of Clinical Epidemiology*

Received Date: 12 December 2016

Revised Date: 17 April 2017

Accepted Date: 2 May 2017

Please cite this article as: Guyatt GH, Ebrahim S, Alonso-Coello P, Johnston BC, Mathioudakis AG, Briel M, Mustafa RA, Sun X, Walter SD, Heels-Ansdell D, Neumann I, Kahale LA, Iorio A, Meerpohl J, Schünemann HJ, Akl EA, GRADE guidelines 17: Assessing the Risk of Bias Associated with Missing Participant Outcome Data in a body of evidence, *Journal of Clinical Epidemiology* (2017), doi: 10.1016/j.jclinepi.2017.05.005.

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**GRADE guidelines 17: Assessing the Risk of Bias Associated with Missing
Participant Outcome Data in a body of evidence**

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Conflict of interest

All authors have completed the ICMJE uniform disclosure form and declare: no support from any organisation for the submitted work; no financial relationships with any organisations that might have an interest in the submitted work in the previous three

years. They declare being involved in previous publications making recommendations on the topic missing participant outcome data.

Funding

This paper is part of a project on addressing missing trial participant data in systematic reviews funded by the Cochrane Collaboration. PA-C was funded by a Miguel Servet research contract from the Instituto de Salud Carlos III (CP16/00137). AGM was funded by a Fellowship in Guidelines Methodology by European Respiratory Society (MTF 2015 - 01). The funders were not involved in study design and the collection, analysis, and interpretation of data and the writing of the article and the decision to submit it for publication. The researchers are independent from funders and had full access to all the data.

Contribution of authors

GG, SE, PAC, BCJ, RAM, SDW, and EA contributed to the conception and design of the paper.

GG, SE, PAC, BCJ, AGM, MB, RAM, XS, SDW, DHA, IN, LAK, AI, JJM, HJS and EAA contributed to the analysis and interpretation of the data.

SDW and DHA contributed to the statistical expertise.

GG contributed to drafting of the article.

GG, SE, PAC, BCJ, AGM, MB, RAM, XS, SDW, DHA, IN, LAK, AI, JJM, HJS and EAA contributed to the critical revision of the article for important intellectual content.

GG, SE PAC, BCJ, AGM, MB, RAM, XS, SDW, DHA, IN, LAK, AI, JJM, HJS and
EAA contributed to the final approval of the article.

ACCEPTED MANUSCRIPT

Abstract

Objective: To provide GRADE guidance for assessing risk of bias across an entire body of evidence consequent on missing data for systematic reviews of both binary and continuous outcomes.

Study design: Systematic survey of published methodological research, iterative discussions, testing in systematic reviews, and feedback from the GRADE Working Group.

Results: Approaches begin with a primary meta-analysis using a complete case analysis followed by sensitivity meta-analyses imputing, in each study, data for those with missing data, and then pooling across studies. For binary outcomes we suggest use of “plausible worst case” in which review authors assume that those with missing data in treatment arms have proportionally higher event rates than those followed successfully. For continuous outcomes, imputed mean values come from other studies within the systematic review, and the standard deviation from the median standard deviations of the control arms of all studies.

Conclusions: If the results of the primary meta-analysis are robust to the most extreme assumptions viewed as plausible, one does not rate down certainty in the evidence for risk of bias due to missing participant outcome data. If the results prove not robust to plausible assumptions, one would rate down certainty in the evidence for risk of bias.

Keywords:

GRADE, missing participant data, risk of bias, systematic reviews, trials

Running title:

GRADE approach to assess risk of bias associated with missing participant data in systematic reviews

Word count:

4,419

What's new?

Key points:

- When assessing risk of bias associated with participant outcome data across an entire body of evidence, we propose using a complete case analysis for the primary meta-analysis.
- When the results of the primary meta-analysis suggest a statistically significant treatment effect, conduct sensitivity meta-analyses using plausible assumptions to impute events in participants with missing outcome data in each study, and then pool across studies.
- If the results of the primary meta-analysis are robust to the most extreme plausible assumptions, one does not rate down certainty in the evidence for risk of bias due to missing participant outcome data.
- If the results are not robust to plausible assumptions, one would rate down certainty in the evidence for risk of bias.

Introduction

The extent to which risk of bias associated with missing participant outcome data (hereafter, missing data) reduces confidence in results represents a key issue for all systematic reviews^{1,2}. Currently, the Cochrane Collaboration Handbook³ focuses on determining whether individual studies are at low or high risk of bias with respect to missing data. When considering whether to rate down for risk of bias across an entire body of evidence, this approach suffers limitations. Assume, for instance, that one sets a threshold of 10% missing data for high risk of bias, and of 6 studies in a meta-analysis 3 have no missing data and 3 have 12% missing data. How is one to decide whether, across the entire body of evidence, one should – or should not – rate down for risk of bias due to missing participant data?

Sensitivity meta-analyses based on different assumptions can address these issues, particularly if such analyses consider issues beyond simply the frequency of missing data, such as the event rate in the intervention and control groups, the distribution of missing data in intervention and control groups, and the reasons for missingness. The Cochrane Handbook encourages such analyses, but with respect to missing data does not provide specific guidance regarding how to proceed.

Three prior publications have filled this gap by presenting approaches for systematic reviews of randomized trials to address missing data for binary⁴ and continuous outcomes^{5,6}. With some modifications, the GRADE Working Group has endorsed these approaches as GRADE guidance to assess the risk of bias associated with missing data in

systematic reviews. In this article, we summarize our modified approaches, providing sufficient detail for their application, and provide several illustrative examples.

We present approaches for three situations: binary outcomes; continuous outcomes in which all studies have used the same instruments; and continuous outcomes in which studies have used different instruments to measure the same construct. In each case, the goal is to make inferences for the entire body of evidence for a particular outcome with respect to risk of bias. Within the GRADE framework, the issue is whether reviewers should rate down certainty in the evidence (quality of evidence, or confidence in evidence) for risk of bias due to missing data.

Development of methods

In developing our approaches, we formed a group consisting of clinical epidemiologists, methodologists, and biostatisticians, all with extensive experience in systematic reviews. We conducted a systematic survey of the literature addressing possible approaches to handling missing data when conducting a meta-analysis⁷⁻⁹. Iterative discussions among the investigators and testing our approaches in a number of systematic reviews completed the process.

The GRADE Working Group reviewed the approaches at a meeting in Vienna in October 2015, providing feedback that led to modifications from what had been previously published. The Working Group reviewed the resulting modifications, and a draft of this

paper, at a subsequent meeting in May 2016 and there approved the approaches as GRADE guidance.

Scope and definitions

This guide is for meta-analyses of trial-level data and does not address methods for meta-analyses of individual participant data that may be available to investigators. We deal only with missing data, and not other elements of risk of bias in a body of evidence (e.g., allocation concealment, blinding) that systematic review authors must address.

We define participant outcome data as ‘missing’ if it is unavailable to the reviewers; i.e., unavailable to investigators of the primary studies, or available to the primary study investigators but not included in published reports and not provided after inquiry. A common problem when dealing with missing data is identifying whether a group of participants (e.g., those who withdrew consent or violated the protocol) have missing data or not.¹⁰⁻¹² Another problem is that the trial authors are sometimes not clear about how they dealt with participants missing data in their analysis (e.g., excluded them, or made assumptions).^{10 13} Prior to applying our approach, we recommend making all possible efforts to obtain unreported but potentially available outcome data from primary study authors, or at least understand how they dealt with missing data.

For conceptual clarity, we distinguish the issue of handling of missing participant outcome data from that of intention to treat (ITT) analysis.¹⁴ The basic principle of ITT involves analyzing participants with available data in the arm to which they were

randomized. A methodological survey found a large variation in the definition of ITT: some suggest ITT is only possible with complete follow-up; some demand imputation of missing data for an ITT analysis; and some take our position that ITT should be restricted to how one handles participants with available data, and that dealing with missing data should be treated as a separate issue.⁷ Thus, what follows begins with a complete case analysis, and deals with missing data as a separate issue best addressed in sensitivity analyses.

Common Elements of the Approaches

We recommend, as do other authors who have written about the issue of missing data in the context of meta-analyses, that systematic review authors' primary analysis include only those for whom data are available (complete case analysis)⁷. An alternative is to use imputation approaches for the primary analysis, an option that is particularly attractive if investigators have strong hypotheses regarding the direction and magnitude of bias associated with missing data. Generating these alternative estimates requires considering the uncertainty associated with imputation and this consideration demands sophisticated statistical approaches. Such approaches are now available for both binary¹⁵ and continuous variables¹⁶.

For outcomes of putative benefit of an experimental intervention, we recommend the approaches primarily, if not exclusively, for meta-analyses in which the results suggest a statistically significant treatment effect. The purpose of the analyses is to challenge the robustness of the inference that a benefit with respect to a particular outcome does indeed

exist. The approaches involve a series of progressively more stringent imputations of data in primary studies, postulating that results from participants with missing data are less favorable to the intervention than results from participants for whom the data are available. One then pools across studies to determine the impact on the point estimate and confidence interval.

For outcomes of harm (i.e. that suggest treated patients are worse off), one may challenge in a similar way the inference that apparent harm with respect to a particular outcome does indeed represent a real effect. To do so, one imputes data attributing a lower rate of adverse events in the treatment group. Alternatively, or in addition, one may attribute a higher rate of adverse events in the control group to participants with missing data than in those in whom the data are available.

In addition, one may be interested in the robustness of inferences that an intervention is not harmful. To address this issue, one would impute data suggesting a higher rate of adverse events in the treatment group. Alternatively, or in addition, one may attribute a lower rate in the control group among participants with missing data than in those in whom the data are available.

Finally, one may challenge failure to establish benefit. This would involve imputing a higher success rate in treatment group patients with missing data than in those followed and/or a lower success rate in control patients with missing data than in those followed.

Binary outcomes

Traditional imputations: There are many possible ways to impute missing data in individual primary studies. One might assume that all participants with missing data in either group had events, that no participants with missing data had events, or a worst-case scenario in which all participants with missing data in the intervention group suffered adverse events but none of the participants in the control group suffered such events. That worst-case scenario calculation assumes that the results of the primary analysis are suggesting the intervention reduces the incidence of the outcome of interest.

Imputations using ratios: Our suggested imputation strategy is based on making assumptions regarding the events in those with missing data as a ratio relative to those with available data in the same arm. Three such ratios have been proposed: the incidence of outcome events in participants with missing data relative to those with complete follow-up ($RI_{MPD/FU}$)¹⁷, the informative missingness odds ratio (IMOR)^{15 18 19}, and the Bayesian version of the IMOR²⁰. In this paper, we use $RI_{MPD/FU}$ when providing illustrative examples. In positive trials one might challenge the robustness of the results by imputing $RI_{MPD/FU} > 1$ in the intervention group and $RI_{MPD/FU} < 1$ in the control group. For instance, an event rate of 10% in participants with available data and a $RI_{MPD/FU}$ of 1.5 would result in an imputed event rate in those with missing data of 15%. An event rate of 20% in control participants with available data with a $RI_{MPD/FU}$ of 0.5 would result in an imputed event rate in those with missing data of 10%. Similarly to the $RI_{MPD/FU}$, the IMOR describes the relationship between the unknown odds among participants with

missing data and the known odds among participants with available data.¹⁵ It differs in the use of odds instead of risks.

In trials suggesting an apparent benefit, for the sake of simplicity we suggest a constant $RI_{MPD/FU}$ of 1.0 for control group missing participants (i.e. assume the same event rate in those with missing as those with available data). For treatment group participants with missing data one might start with the least stringent assumptions (for instance a $RI_{MPD/FU}$ of 1.5) and repeat the meta-analysis with the associated individual primary study results. If imputed data does not materially affect the results (in particular, confidence intervals continue to exclude a null effect) one might then examine the impact of progressively more stringent but less plausible assumptions ($RI_{MPD/FU}$ of up to 3.0, or possibly 5.0).

We have used 5.0 as the most stringent but still plausible $RI_{MPD/FU}$ because we identified one study in which participants lost to follow-up were subsequently found to have had 5 times the rate of events than followed-up participants, but none that reported a higher ratio²¹. We refer to the meta-analysis using the plausible most stringent $RI_{MPD/FU}$ as the “plausible worst case”. The reviewers should ideally select the value of the plausible most stringent $RI_{MPD/FU}$ *a priori*. The choice will be based on factors such as the clinical scenario (e.g., higher value of $RI_{MPD/FU}$ in a trial of cardiac transplant in which participants are more likely to have suffered a bad outcome if lost to follow-up), and the baseline prognostic profile of participants with missing participant outcome data, when reported.

To the extent that pooled estimates remain similar when making progressively more stringent assumptions (and in particular, results remain statistically significant), one would conclude that the results are robust to the missing data and, in the GRADE framework, not rate down certainty in the evidence for risk of bias. If results change materially, and particularly if statistical significance is lost, one would rate down certainty in the evidence for risk of bias due to missing data. In general, one would be more willing to rate down if significance is lost with the less stringent assumptions.

Illustrative examples: We have used this approach in several recently published Cochrane and non-Cochrane reviews²²⁻³². One of these studies assessed probiotics for the prevention of *Clostridium difficile* infection (CDI)²⁸. In 13 of 20 included randomized trials, data on CDI were missing for 5% to 45% of participants. We assumed that the event rate was the same among control group participants with missing data and participants that were successfully followed. For the probiotic group, we re-calculated pooled treatment effects by using our assumed RI in participants with missing data compared with those who were successfully followed using the following assumptions: $RI_{MPD/FU}$ 1.5, 2.0, 3.0 and 5.0. Our results proved robust to each of the RI assumptions, and even with the 5.0 ratio, the probiotic effect remained large and the 95% CI narrow (relative risk, 0.50 [0.34 to 0.76]) (Appendix Figure 1).

The Appendix provides another example of applying the method to a benefit outcome with binary data and shows how the decision to rate down certainty in the evidence for

risk of bias due to missing data can vary across outcomes within the same study (Example 2, Figures 2 and 3).

Application to harms: One could apply a similar approach to outcomes for which the results suggest harm with the experimental treatment, but in this case impute a $RI_{MPD/FU}$ of less than 1.0 to treatment and ≥ 1.0 to control. Our suggestion, in parallel to that for benefit outcomes, is to assume $RI_{MPD/FU}$ of 1.0 for control, and a value as low as 0.20 in the intervention group. Alternatively, one could impute a $RI_{MPD/FU}$ for the intervention group and $RI_{MPD/FU}$ of > 1.0 for the control group. Example 3 in the Appendix provides an illustration of use of both options.

Application to non-statistically significant results: One could also apply the approach to determine if findings of no increase in harm are robust. This would involve the same approach as in the benefit setting: assume a $RI_{MPD/FU}$ of 1.0 in control participants with missing data and > 1.0 in treatment group participants with missing data, possibly as high as 5.0. Again, one would examine whether results change appreciably and in particular whether previous results that were not significant become significant. Appendix Example 4 provides an illustration.

We have created a freely downloadable Excel document that allows a systematic review author to determine the numerators and denominators to be used for each trial included in the meta-analysis according to the selected assumptions:

<https://www.dropbox.com/s/opstwgm45qiq57k/Assumptions%20about%20MPD%20v5.xls?dl=0>

Binary outcomes – choosing the stringency of the imputations

Investigators using our approaches will need to decide on which extreme a $RI_{MPD/FU}$ they are willing to consider plausible. The choice will be based on factors such as the clinical scenario (e.g., higher value of $RI_{MPD/FU}$ in a trial of cardiac transplant in which participants are more likely to have suffered a bad outcome if lost to follow-up). Another consideration will be the frequency of the event of interest. If it is infrequent (say, 5%) it may be reasonable to assume a maximum $RI_{MPD/FU}$ of 5, and thus an event rate in those with missing data of 25%. If it is frequent (say 40%) a $RI_{MPD/FU}$ of even 3 results in a 100% event rate in those lost. One may conclude that a rate of 100% is not plausible, in which case a maximum $RI_{MPD/FU}$ of only 2 may be appropriate.

Continuous outcomes – all studies using the same measure

Addressing risk of bias consequent on missing data in systematic reviews addressing continuous outcomes provides additional challenges, including the necessity of imputing both means and standard deviations. Once again, we suggest the primary meta-analysis use only participants with available outcome data (complete case). When pooled estimates are statistically significant, we suggest sensitivity meta-analyses imputing outcome data that are missing, to challenge the robustness of these pooled estimates.

To impute means, we consider five possible sources of data. In characterizing these sources, we use “best” to describe the most desirable health state (which could be a high or low score) and “worst” to describe the least desirable health state.

- A. The best mean score among the intervention arms of the eligible trials.
- B. The best mean score among the control arms of the eligible trials.
- C. The mean score from the control arm of the trial under consideration.
- D. The worst mean score among the intervention arms of the eligible trials.
- E. The worst mean score among the control arms of the eligible trials.

To test the robustness of a pooled estimate showing an apparent benefit, using the five suggested sources of data above, we recommend four imputation strategies that will almost always be progressively more stringent. Table 1 provides a matrix describing the four strategies:

- Strategy 1 uses source C for missing data in both the intervention and control arms.
- Strategy 2 uses source D for missing data in the intervention arm, and source B for missing data in the control arm.
- Strategy 3 uses source E for missing data in the intervention arm, and source B for missing data in the control arm.
- Strategy 4 uses source E for those with missing data in the intervention arm, and source A for missing data in the control arm.

Table 1. Matrix of assumptions for participants with missing data for continuous outcomes in intervention and control arms

Assumptions about the means of participants with missing data		Assumptions about the means of participants in intervention arm				
		Source A	Source B	Source C	Source D	Source E
Assumptions about the means of participants in control arm		Source A				Strategy 4
	Source B				Strategy 2	Strategy 3
	Source C			Strategy 1		
	Source D					
	Source E					

Source A, best mean among intervention arms of included trials; Source B, best mean among the control arms of included trials; Source C, mean score from the control arm of the same trial; Source D, worst mean among the intervention arms of included trials; Source E, worst mean among control arms of included trials.

We tested a number of sources of measures of variability (standard deviations) for the imputed data and found they yielded very similar results. We therefore suggest the simplest and most plausible source of data, the median SD in the control group of all included trials.

To generate a pooled estimate across trials using the imputed data, we suggest, for each arm in each trial, pooling the observed means and SDs of the participants with available data with the imputed means and SDs for participants with missing data using the following formulas:

$$1. M_{XTi} = \frac{(M_{FTi} \times n_{FTi}) + (M_{LTi} \times n_{LTi})}{n_{FTi} + n_{LTi}}$$

$$2. M_{XCi} = \frac{(M_{FCi} \times n_{FCi}) + (M_{LCi} \times n_{LCi})}{n_{FCi} + n_{LCi}}$$

$$3. SD_{XTi} = \sqrt{\frac{(n_{FTi} - 1)SD_{FTi}^2 + (n_{LTi} - 1)SD_{LTi}^2}{n_{FTi} + n_{LTi} - 2}}$$

$$4. SD_{XCi} = \sqrt{\frac{(n_{FCi} - 1)SD_{FCi}^2 + (n_{LCi} - 1)SD_{LCi}^2}{n_{FCi} + n_{LCi} - 2}}$$

$$5. n_{XTi} = n_{FTi} + n_{LTi}$$

$$6. n_{XCi} = n_{FCi} + n_{LCi}$$

where “M” represents the mean, “SD” the standard deviation, “n” the group size, “X” the combined estimates, “F” the followed-up group, “L” the lost to follow-up group, “T” the treatment group, “C” the control group, and “i” the trial.

For each study, one can then calculate the treatment effect – a mean difference - by combining means and SDs from the treatment and control arms using a fixed effects model. One can then pool treatment effects across studies using, according to one’s preference, either a standard fixed effect or random effects meta-analysis, to generate the mean difference across all included studies.

As was the case for the approach to binary data, if results were robust (statistical significance maintained even with the most stringent assumptions one considers plausible) one would not, within the GRADE framework, rate down certainty in the

evidence for risk of bias. If statistical significance were lost for any of the more stringent plausible approach, one would rate down. Our prior papers⁴⁻⁶ provide examples of use of the approach to challenging the robustness of findings of apparent benefit, as do Examples 5 and 6 in the Appendix.

One could apply a similar approach to harm outcomes in which the results suggest harm with the experimental treatment. In this case, the approach would involve imputing more favourable results (less harm) to those in the intervention group with missing data, and less favourable results to control group participants with missing data. The most extreme challenge would be to attribute the best mean available from either group to intervention participants with missing data, and the worst intervention group mean to control participants with missing data.

One could also apply the approach to determine if findings of no [statistically significant] increase in harm are robust. In this case, the approach would involve imputing unfavourable results (greater harm) to those in the intervention group with missing data, and favourable results to control group participants with missing data. The most extreme challenge would be to attribute the worst mean (whether it comes from intervention or control) to intervention participants with missing data, and the best mean (whether from intervention or control) to control participants with missing data. Example 7 in the Appendix provides an illustration.

We have created a freely downloadable Excel document that allows a systematic review author to determine the means and SDs to be used for each trial included in the meta-analysis according to the selected assumptions per strategy:

https://www.dropbox.com/s/3ie12qfwjnfwx0z/MPD%20for%20continuous%20outcomes_Template.xlsx?dl=0

Continuous outcomes – studies using different measures

For certain continuous outcomes and in particular participant-important outcomes focusing on issues such as health-related quality of life (HRQL), clinical trial investigators often choose alternative measures of the same underlying construct. For example, there are at least five instruments available to measure HRQL in participants with chronic obstructive pulmonary disease (COPD) (Chronic Respiratory Questionnaire, Clinical COPD Questionnaire, Pulmonary Functional Status and Dyspnea Questionnaire, Seattle Obstructive Lung Disease Questionnaire, and the St. Georges Respiratory Questionnaire)³³. The use of different instruments requires a modification of the methods described in the previous section.

We suggest, for this modified approach, choosing a single reference measurement instrument, converting scores from different instruments to the units of the reference instrument, and then proceeding with imputation of missing values, combining the available data with estimates from the missing data for each study, and then pooling across studies.

Alternatively, one might proceed exactly as in the example when all studies use the same instrument, but instead of natural units use the standardized mean difference (SMD). Because of limitations of the SMD both with respect to vulnerability to varying between-study heterogeneity, and its interpretability³⁴, we prefer to base calculations on choosing a single reference instrument as described in the following.

We suggest two key criteria when choosing the reference instrument. The first is its frequency of use, and thus its familiarity to the target audience. The second criterion is the measurement properties of the instrument. In the context of clinical trials, the key measurement properties are instrument longitudinal validity (correlations of change with other related measures), responsiveness (ability to detect important change over time, even if that change is small), and interpretability (typically, an established anchor-based minimally important difference)³⁵. Details of the application of the approach follow.

Once one has chosen the reference instrument, one must convert all results into the units of that instrument. Let us say that A represents the reference instrument and B represents an alternative instrument. To convert B units to A units, one first converts the means and standard deviations (SDs) of the scores from instrument B to the units of instrument A³⁶ using the following formula:

$$M_{Ai} = (M_{Bi} - L_B) \times (R_A \div R_{Bi}) + L_A \text{ and}$$

$$SD_{Ai} = SD_{Bi} \times (R_{Ai} \div R_{Bi}),$$

where M represents the mean, L_A and L_B represent the worst possible outcome score of instrument A and B, respectively, R_A and R_B the ranges (the highest possible outcome score minus the lowest possible outcome score) for instruments A and B, respectively, and i the trial. One applies these formulas separately to the intervention group and the control group of each trial⁶. One then proceeds exactly as in the previous section using the converted score.

Alternative Threshold for Rating down for Risk of Bias: The Context of Healthcare Guidelines

In the discussion thus far, we have suggested an approach to rating down using only one threshold: the 95% confidence interval includes a relative effect of 1.0, or an absolute difference of 0. This threshold corresponds to the p-value including the traditional boundary of 0.05.

This is not the only threshold one might use. Instead, one might choose the smallest effect that patients are likely to consider important, and apply the approach to that threshold.

For instance, consider the outcome of prevention of a myocardial infarction. Even for an intervention associated with small burden and toxicity, patients are unlikely to choose the treatment if effects were very small (e.g. a reduction in infarction of only 1, or perhaps

even 5 in 1,000). If, however, the intervention is associated with large burden and toxicity, the threshold would be much higher (10, or perhaps even 20 or more in 1,000).

Applying this logic to the latter situation, and choosing a threshold of 20 in 1,000, were the boundary of the confidence interval closest to no effect to remain greater than 20 in 1,000 for even the most stringent imputation, one would not rate down certainty in the evidence for risk of bias. If, however, the confidence interval in an imputation considered plausible included the threshold of benefit of 20 in 1,000 (that is, included reductions in infarction of less than 20 in 1,000, even if it remained above an effect of 0) one would rate down certainty in the evidence for risk of bias.

Because choosing a threshold other than no effect involves a value judgment – the choice depends on the importance placed on the target outcome (in the example myocardial infarction) and the importance placed on the burden and toxicity – this approach may be best applied in the context of a meta-analysis associated with a healthcare guideline. It will also be restricted to consideration of absolute rather than relative effects. We have applied this approach presented in one of our prior articles⁶.

Dealing with Limitations in Reporting

Systematic review authors will find challenges when authors of primary studies fail to adequately report missing data.³⁷ For example, trial authors may not clearly report whether they imputed outcomes for participants with missing data. Consequently, a

sensitivity analysis making imputations for participants with missing data risks double counting. Elsewhere, we have described in detail the solutions for a number of these challenges³⁷. For trials in which authors do not report the frequency of missing data, we suggest using the median missing data rate from all trials included in the review. If one perceives this assumption is too stringent, alternatives include a sensitivity analysis using a missing participant data rate of zero in both arms.

For trials in which authors fail to report missing data for each study arm and report total missing data only, we suggest assuming the same rate of missing data in both intervention and control groups. For trials in which the authors report a single imputed analysis only, we suggest using the imputed results for both primary and sensitivity analyses. Reviewers should acknowledge such limitations when discussing the results of sensitivity analyses related to missing data.

Discussion

We have developed structured and transparent approaches to determine the extent to which missing data across an entire of evidence introduces risk of bias and thus threatens the certainty in the evidence in systematic reviews. Our approaches to binary outcomes, and to continuous data when all studies use the same outcome measure, do not require a high level of statistical sophistication, and can be carried out relatively easily in many statistical programs including RevMan. Our approach to continuous data when studies use different outcome measures begins with converting all instruments to the units of a common instrument, requires greater statistical sophistication, but is nevertheless

straightforward. The approaches have received GRADE working group endorsement, and their use in any systematic review using GRADE approaches would be desirable.

The analyses that we describe are sensitivity analyses designed to facilitate inferences regarding risk of bias, rather than to generate alternative best estimates of intervention effects. Thus, the approaches do not need to deal with the uncertainty associated with the imputed values.

The approaches assume that investigators have little idea about the direction that bias as a result of missing data may take, hence the use of complete case approach in the primary meta-analysis. If investigators opt to make imputations in the primary analyses (as discussed earlier) they should consider the uncertainty associated with imputation using the appropriate statistical approaches for both binary¹⁵ and continuous variables¹⁶.

Our approaches all require judgment regarding what is and is not plausible; judgments some may find arbitrary. Our approaches do, however, permit multiple progressively more stringent sensitivity analyses. This allows investigators – and users of meta-analyses – to choose the most extreme threshold that they consider plausible, and then determine whether results are robust to that threshold.

We make specific suggestions for thresholds of plausibility – thresholds other than those we suggest may be more appropriate in individual meta-analyses. For instance, for continuous variables, one might not choose the most extreme results from other studies,

but results adjacent to or near the extremes. Investigators concerned about confidence intervals being excessively narrow as a result of not taking into account uncertainty in imputations may choose more stringent thresholds. In general, for any particular meta-analysis, those who consider extremes more plausible will be more likely to rate down the certainty of the evidence for risk of bias due to missing data than those who do not.

Deciding on specific imputation strategies also entailed some degree of arbitrariness: we opted, where possible, for simplicity. For example, to address apparently beneficial treatment effects in binary outcomes we suggest, for the control group, assuming that event rates in missing participants do not differ from those in participants with complete data. Thus, the only variation is the increase in event rates imputed to missing data, relative to those with complete data, in the intervention group. It is possible, of course, for investigators to reasonably deviate from our guidance and to also vary control group event rates imputed to control groups. Systematic review authors might consider similar reasonable alternatives regarding our suggestions for how to deal with harm outcomes, and with continuous variables.

In our presentation, we have focused on rating down certainty in the evidence for risk of bias only when meta-analyses that include plausible imputations for missing data result in loss of statistical significance. We have also pointed out, however, that one could be even more stringent: one could rate down if the boundary of the confidence interval closest to no effect includes a threshold of patient-importance.

In summary, this GRADE guidance includes structured, transparent, and relatively easily implementable strategies to determine whether the extent of missing data warrants rating down the certainty in a body of evidence for a particular outcome for risk of bias.

Ongoing work involves examining the impact of the approaches on a large sample of meta-analyses, and may inform future updates of this guidance³⁸.

List of Abbreviations:

IMOR: Informative missingness odds ratio

RI: Relative incidence

MPD: Missing participant data

FU: Followed-up

CDI: Clostridium difficile infection

SD: Standard deviation

HRQL: Health-related quality of life

COPD: Chronic obstructive pulmonary disease

SMD: standardized mean difference

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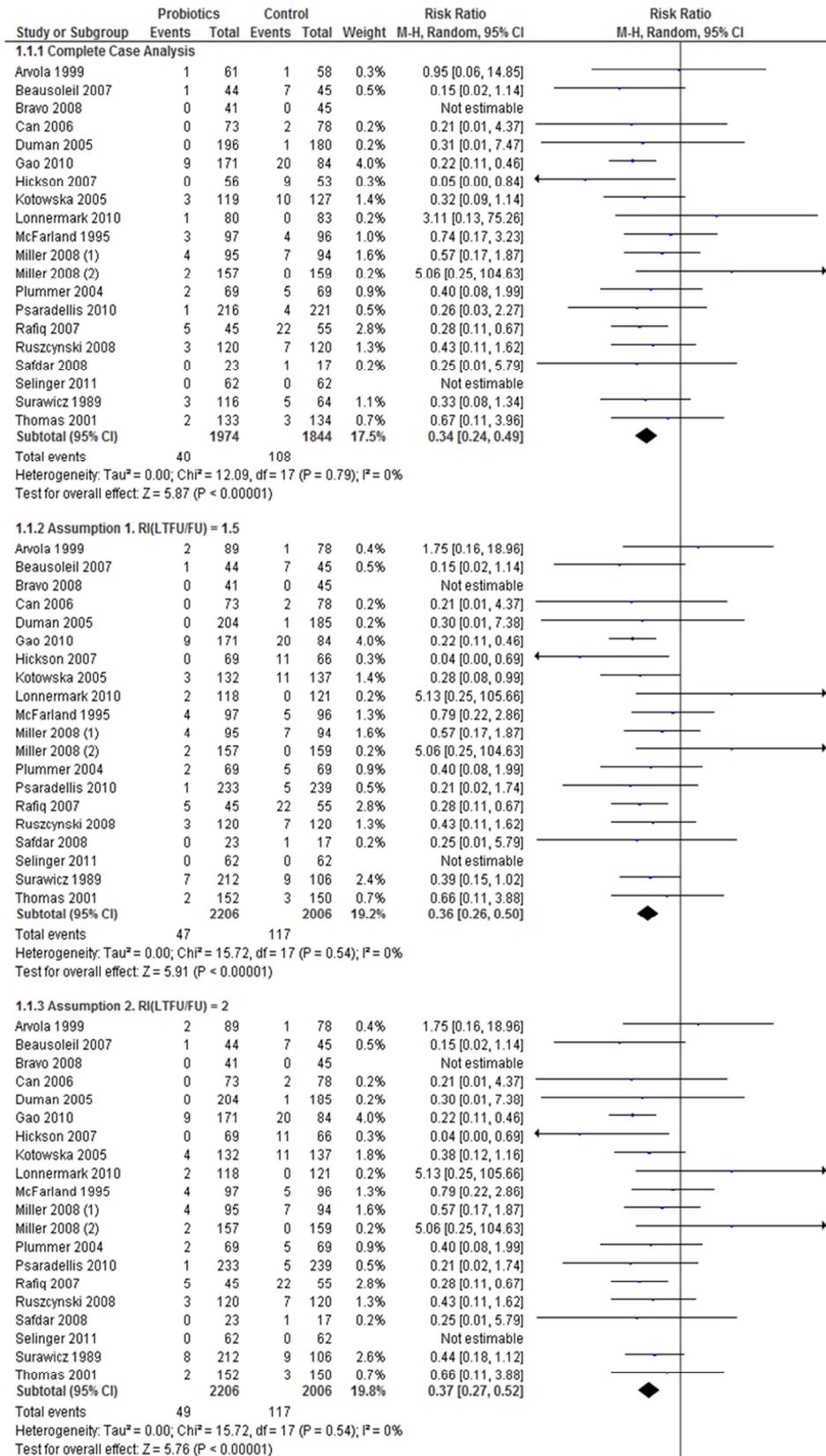
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Appendix

Example 1: Binary outcome, testing robustness of finding of benefit: probiotics for preventing *Clostridium difficile* infection

As described in the text of the article, a systematic review and meta-analysis assessed probiotics for the prevention of *Clostridium difficile* infection (CDI)¹. In 13 of 20 included randomized trials, data on CDI were missing for 5% to 45% of participants. We assumed that the event rate was the same among control group participants with missing participant outcome data (hereafter missing data) and participants that were successfully followed. For the probiotic group, we re-calculated pooled treatment effects by using our assumed RI in participants with missing data compared with those who were successfully followed using the following assumptions: $RI_{MPD/FU}$ 1.5, 2.0, 3.0 and 5.0. Our results proved robust to each of the RI assumptions, and even with the 5.0 ratio, the probiotic effect remained large and the 95% CI narrow (relative risk, 0.50 [0.34 to 0.76]) (Figure 1). We did not rate down for risk of bias as a result of missing participant data.



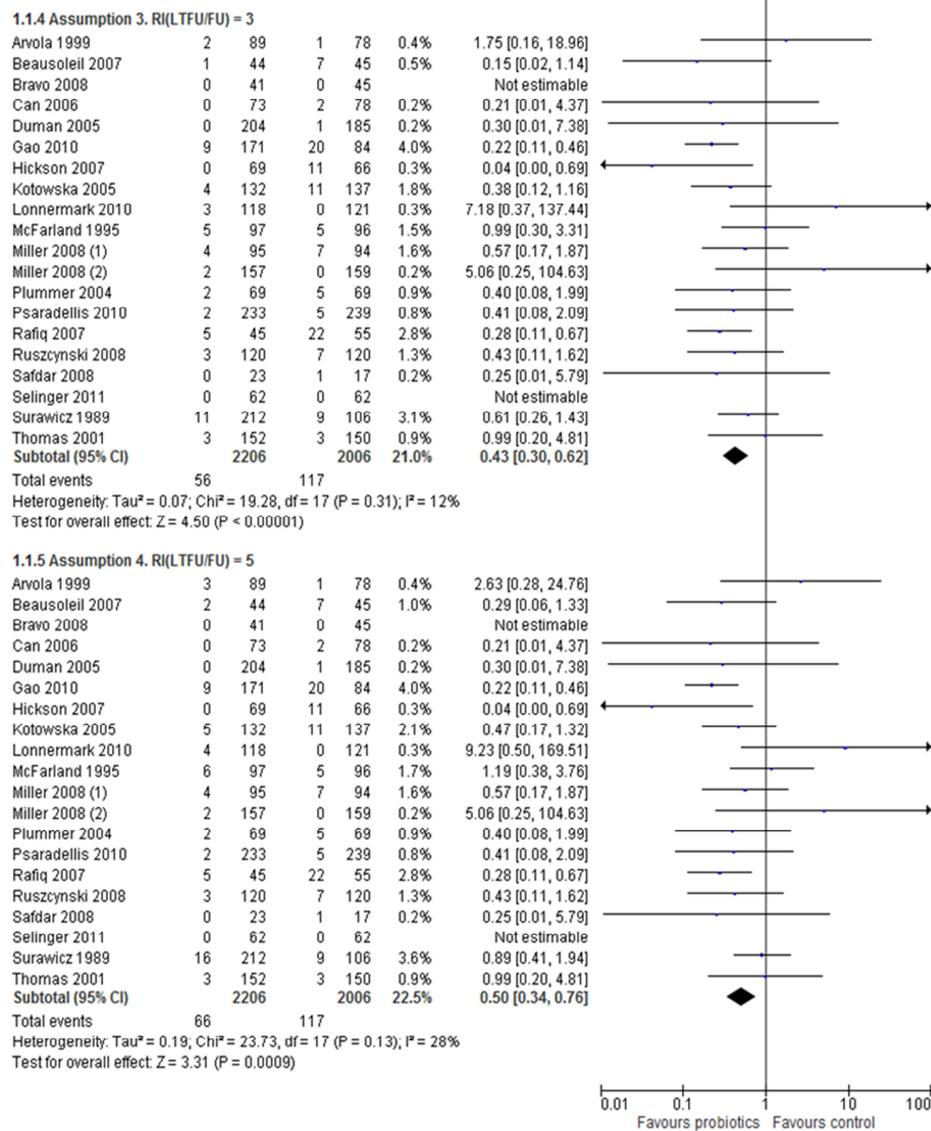


Figure 1. Probiotics for preventing *Clostridium-difficile* associated disease: complete case analysis and sensitivity analyses using plausible assumptions.

Example 2: Binary outcome, testing robustness of finding of benefit: tiotropium versus long-acting beta-agonist in COPD

We assessed the risk of bias in three of the outcomes of a Cochrane review comparing the efficacy and safety of tiotropium versus long-acting beta-2 agonists (LABA) in stable COPD². The reviewers used GRADE to assess the quality of evidence and did not rate down for any of the outcomes as a result risk of bias due to missing data. When authors of the primary studies did not report a complete case analysis or the methods used to handle missing data, we assumed that they had imputed no events for patients with missing data and conducted a complete case analysis accordingly.

For the outcome “Mortality” we did not rate down for risk of bias due to missing data because the investigators, in all eligible studies, determined survival status at the end of follow up in all randomized patients (no missing data in any study).

In this meta-analysis, authors included all randomized patients from every primary in the overall estimates assuming that those with missing data did not have missed events (i.e. including missing patients in the denominator, but not in the numerator). For all meta-analyses reported here, if unclear in either the primary studies or the published meta-analyses, we assumed authors imputed no outcomes of interest for patients with missing data (including them in the numerator, but not the denominator).

For “Exacerbations leading to hospitalization”, authors reported an odds ratio, 0.87 [0.77 to 0.99]. Data were missing for 5% to 11% of the participants.

Both primary authors and the systematic review authors reported an outcome of “adverse events”. For such patients, it was not clear if some of those events were exacerbations leading to hospitalization, nor if individual experiencing adverse events continued to the end of the study or ceased participation at the time of the adverse events. We assumed that the adverse events were not exacerbations leading to hospitalization, and that patients experiencing adverse events were followed to study termination (and thus not missing). We made similar assumptions for other outcomes.

With these assumptions, our complete case analysis generated a pooled OR of 0.83 [0.73, 0.94]. With an overall event rate of 16% in the intervention arm of the meta-analysis, we considered it plausible that the $RI_{MPD/FU}$ ratio could be 1.5, 2.0 or 3.0. A $RI_{MPD/FU}$ of 5.0 was not considered plausible (80% of the participants would have had a hospitalization for an exacerbation). Statistical significance was borderline assuming a $RI_{MPD/FU}$ of 2.0 (odds ratio, 0.89 [0.79 to 1.00]), and it was lost with a $RI_{MPD/FU}$ of 3.0. We would therefore rate down quality for risk of bias due to missing data (Figure 2).

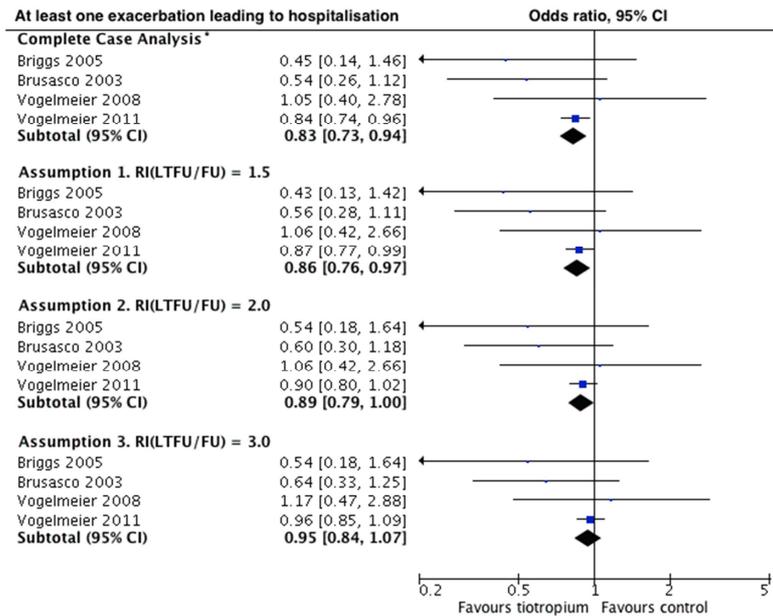


Figure 2. Tiotropium versus long acting beta-2 agonists (LABA) in stable COPD: Hospitalization, complete case analysis and sensitivity analyses using plausible assumptions.

For the outcome “At least one exacerbation during the study period” (odds ratio, 0.86 [0.77 to 0.93]) data were missing for 4% to 20% of the included patients. The overall event rate in the intervention arm of the meta-analysis was 41%. Because higher ratios would result in an imputation in which all patients with missing data in the intervention arm would have had at least one exacerbation (an implausible assumption), we conducted sensitivity analyses assuming that the $RI_{MPD/FU}$ ratio may be 1.5 or 2.0. The results proved robust to each of our $RI_{MPD/FU}$ assumptions; hence, we would not rate down quality for risk of bias due to missing data (Figure 3).

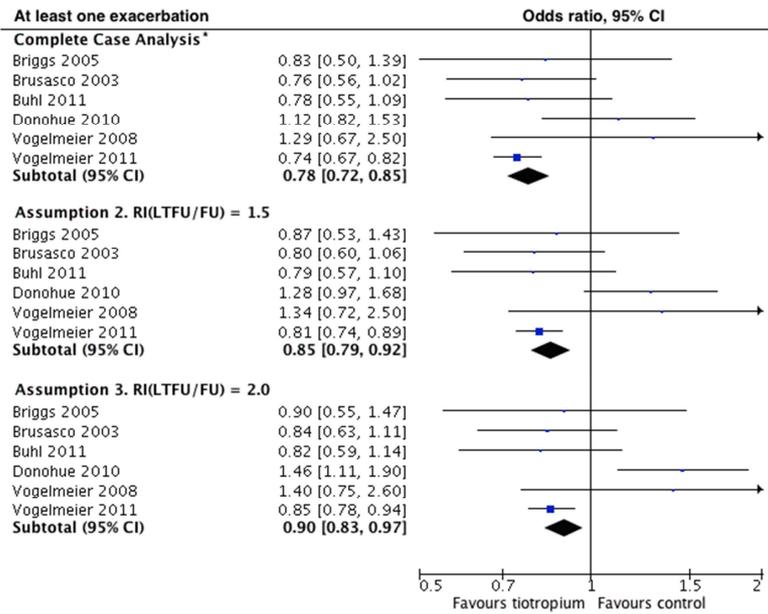


Figure 3. Tiotropium versus long acting beta-2 agonists (LABA) in stable COPD: At least one exacerbation, complete case analysis and sensitivity analyses using plausible assumptions.

Example 3: Binary outcome, testing robustness of finding of harm: tiotropium versus any control in chronic obstructive pulmonary disease

Another meta-analysis assessed the safety of tiotropium versus any control in COPD³. The authors did not use GRADE to assess quality of evidence, but did explicitly conclude that there was a low risk of bias associated with missing data. We assessed the risk of bias associated with missing data for the composite outcome of long-term cardiovascular major outcomes (relative risk, 2.12 [1.22 to 3.67] as reported in the meta-analysis: for patients with missing data, authors assumed they did not have missed events), which included myocardial infarction, stroke and deaths due to cardiac causes. The frequency of missing data in the primary studies was between 11% and 29% but differed between study groups (5%-25% of the patients in the tiotropium and 10%-31% in the control group).

The overall event rate in both arms of the study was very low (2.3% in the intervention, 1.2% in the control arm); we considered plausible $RI_{MPD/FU}$ ratios of 0.7, 0.5, 0.3 and 0.2 in the intervention arm. Results using these assumptions were proved robust. However, given both the low event rate and the higher rate of missing data in the control arm, we performed additional sensitivity analyses, using 1.5, 2.0, 3.0 and 5.0 as $RI_{MPD/FU}$ assumptions in the control arm, and 1 in the intervention arm. The rationale for this analysis was that the larger number of patients with missing data in the control arm could lead to higher risk of bias and a corresponding higher imputed number of events. In this sensitivity analysis, results became non-significant assuming ratios of 2.0 (relative risk, 1.49 [0.96 to 2.30]) or higher (Figure 4). Consequently, we would rate down for risk of bias due to missing data.

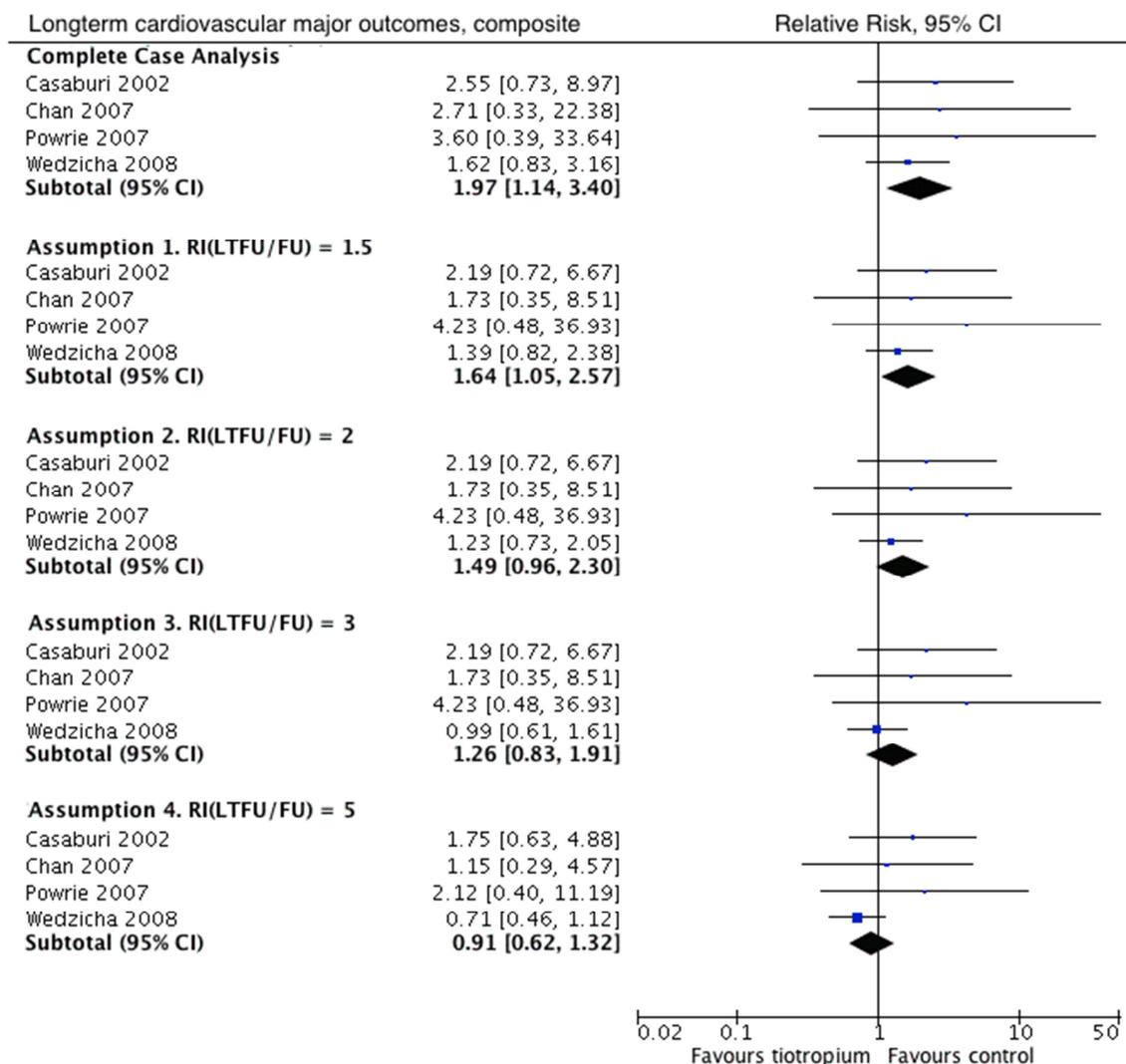


Figure 4. Tiotropium versus placebo in COPD: Myocardial infarction, stroke and cardiovascular mortality, complete case analysis and sensitivity analyses using plausible assumptions.

Example 4: Binary outcome, testing robustness of finding of no harm: tiotropium versus any control in chronic obstructive pulmonary disease

In another meta-analysis, Yohannes and colleagues assessed the efficacy and safety of tiotropium versus any control in chronic obstructive pulmonary disease⁴. One of their findings was that tiotropium was not associated with increased risk of severe adverse events compared to placebo (odds ratio, 1.06 [0.97 to 1.17] as reported in the meta-analysis: patients with missing data included; authors assumed they did not have missed events). The authors did not use GRADE methodology to assess the quality of evidence. The missing data rate was between 5.5% and 18%.

The overall events rate was 39% and 42% in the tiotropium and control arms of the meta-analysis respectively. We assumed that the event rate was the same among patients with missing data and those who were successfully followed in the control arm, and we used plausible assumptions for the $RI_{MPD/FU}$ in the tiotropium arm. Given the high event rates noted, we considered as plausible the RI ratios 1.5 or 2.0, since higher ratios would have led to imputations of all patients with missing data would experiencing a severe adverse event. With our first assumption, the meta-analysis showed a significantly higher risk of severe adverse events associated with tiotropium (odds ratio, 1.12 [1.02 to 1.23]). For this reason we would rate down quality for risk of bias due to missing data (Figure 3).

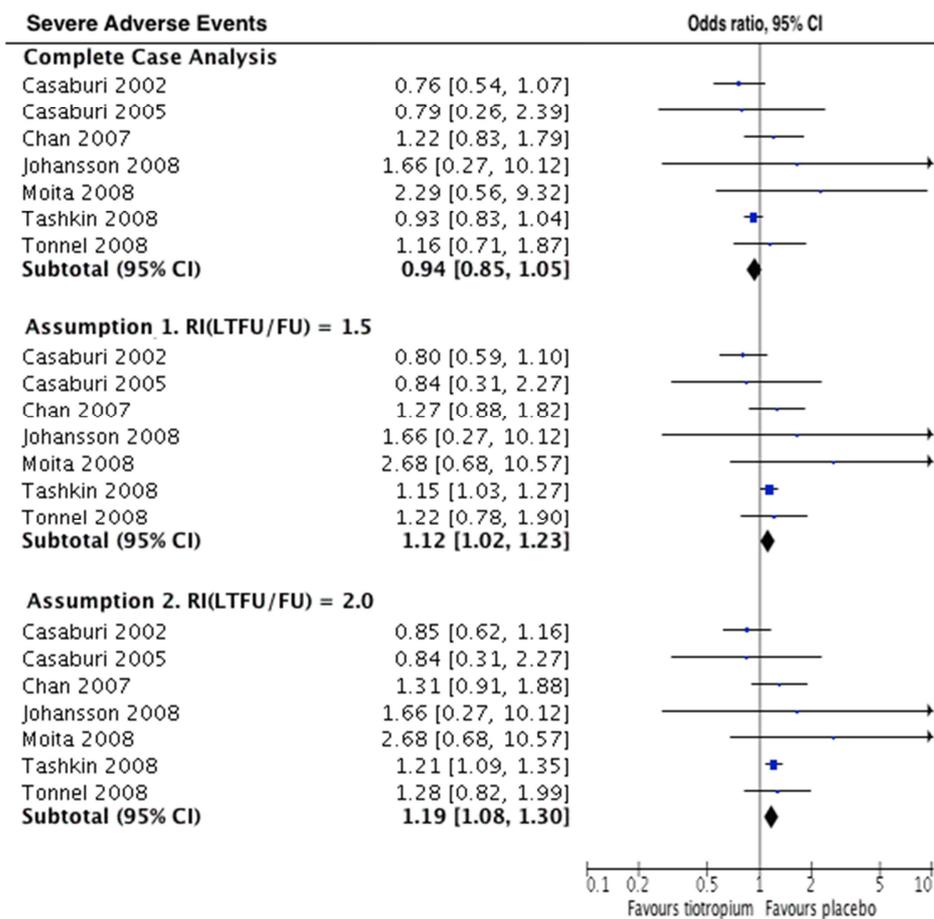


Figure 5. Tiotropium versus placebo in COPD: Severe adverse events, complete case analysis and sensitivity analyses using plausible assumptions.

Example 5: Continuous outcome, testing robustness of finding of benefit: Non-invasive ventilation (NIV) during exercise training in COPD.

A Cochrane review evaluated the impact of NIV during exercise training on the exercise capacity of patients with COPD⁵. One of the outcomes was percentage change in constant work rate endurance time (mean difference 58.68 [3.76 to 113.59], complete case analysis). This meta-analysis included two studies; data were missing for 21.6 and 34.5% of the participants. The reviewers, using GRADE, rated the risk of bias due to missing data as low. We re-assessed this risk using plausible assumptions about the means of participants with missing data in each study arm, following GRADE's guidance. The robustness of the results was lost from our first strategy, where we assumed that the mean scores among missing data in both arms of each included trial was equal to the one from the control arm of the trial under consideration (mean difference 42.94 [-4.79 to 90.68]) and thus we would rate down quality for risk of bias due to missing data (figure 4).

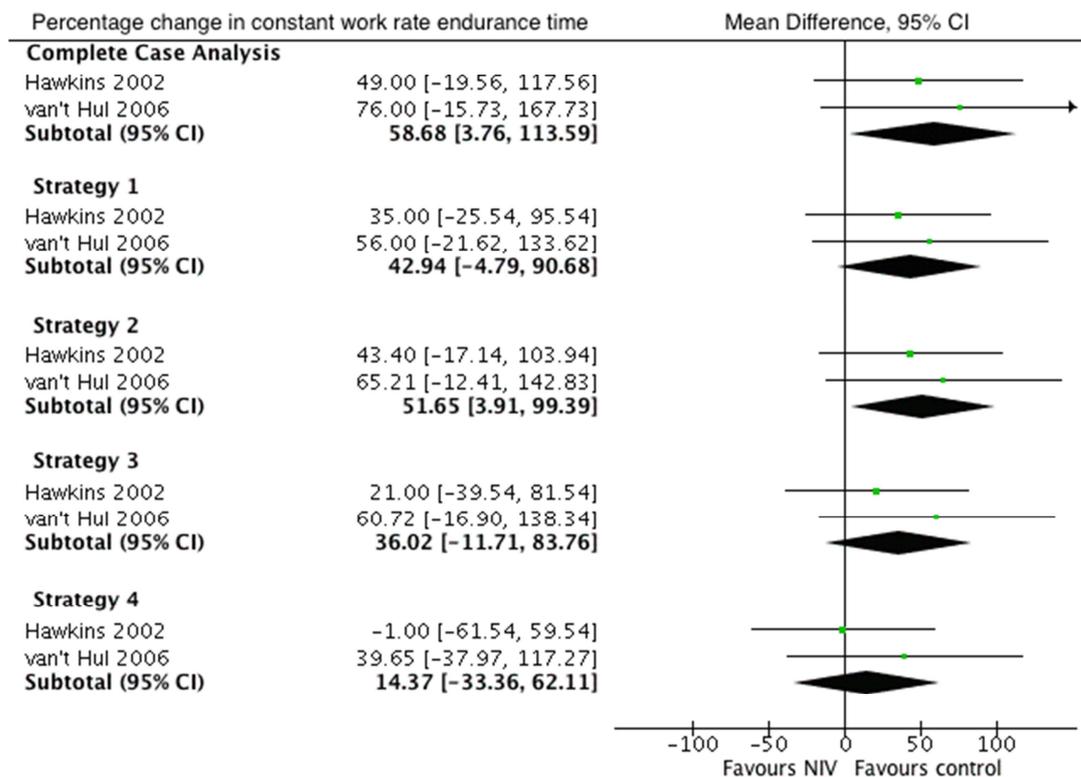


Figure 6. NIV during exercise training in COPD: Constant work rate endurance time, complete case analysis and sensitivity analyses using plausible assumptions.

Example 6: Continuous outcome, testing robustness of finding of benefit: Levothyroxine versus minimally invasive therapies or no treatment for benign thyroid nodules.

A Cochrane review compared Levothyroxine versus minimally invasive therapies or placebo for benign thyroid nodules⁶. The authors compared total thyroxine (T4) at the end of study period with levothyroxine treatment versus no treatment or placebo and demonstrated that levothyroxine treatment is associated with higher total T4 (mean difference 48.28 [35.12, 61.43], with most primary studies using a last available observation carried forward approach to the analysis. This outcome was based on five trials. GRADE was not used; the risk of bias of the included studies was rated as low or unclear. The missing data rate was between 0% and 11.8%. Following GRADE's guidance we re-assessed the risk of bias due to missing data using plausible assumptions about the means of participants with missing data. The result was proved robust to each of the imputation strategies, so we would not rate down quality for risk of bias due to missing data (Figure 8).

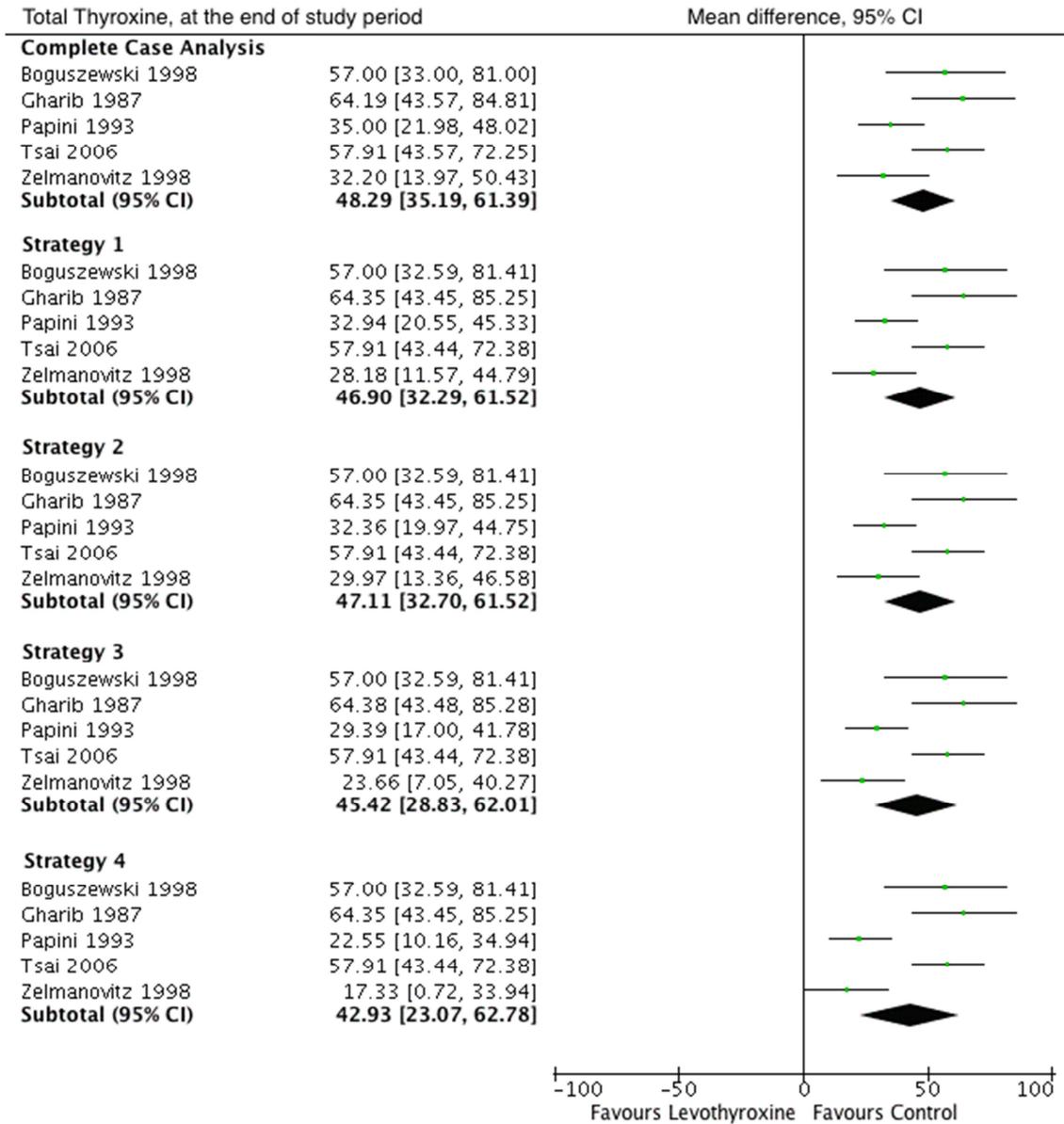


Figure 7. Levothyroxine versus placebo or no treatment for benign thyroid nodules: Total thyroxine at end of study period, complete case analysis and sensitivity analyses using plausible assumptions.

Example 7: Continuous outcome, testing robustness of finding of no harm: Different durations of corticosteroid therapy for exacerbations of COPD

Another Cochrane review compared shorter versus longer duration of corticosteroid therapy for exacerbations of COPD⁷. One of the outcomes was degree dyspnea at the end of intervention, measured with the Medical Research Council (MRC) scale; no significant between group difference was demonstrated (mean difference -0.08 [-0.34, 0.17], complete case analysis, positive values favoring the longer course of steroids). This outcome was based on two trials. The reviewers did not use GRADE for this outcome, but they rated the risk of bias due to missing data low for both trials. Data were missing for 5.6% and 5.8% of the participants. Following GRADE's guidance. We re-assessed the risk of bias due to missing data using plausible assumptions about the means of participants with missing data. The second suggested strategy, using the worst mean score among the intervention arms of eligible trials for the participants with missing data in the intervention group and the best mean score among the control arms of eligible trials in the control group, resulted in a significant decrease in the degree of dyspnea with shorter courses of steroids (mean difference -0.61 [-0.86 to -0.37]). Consequently, we would rate down quality for risk of bias due to missing data.

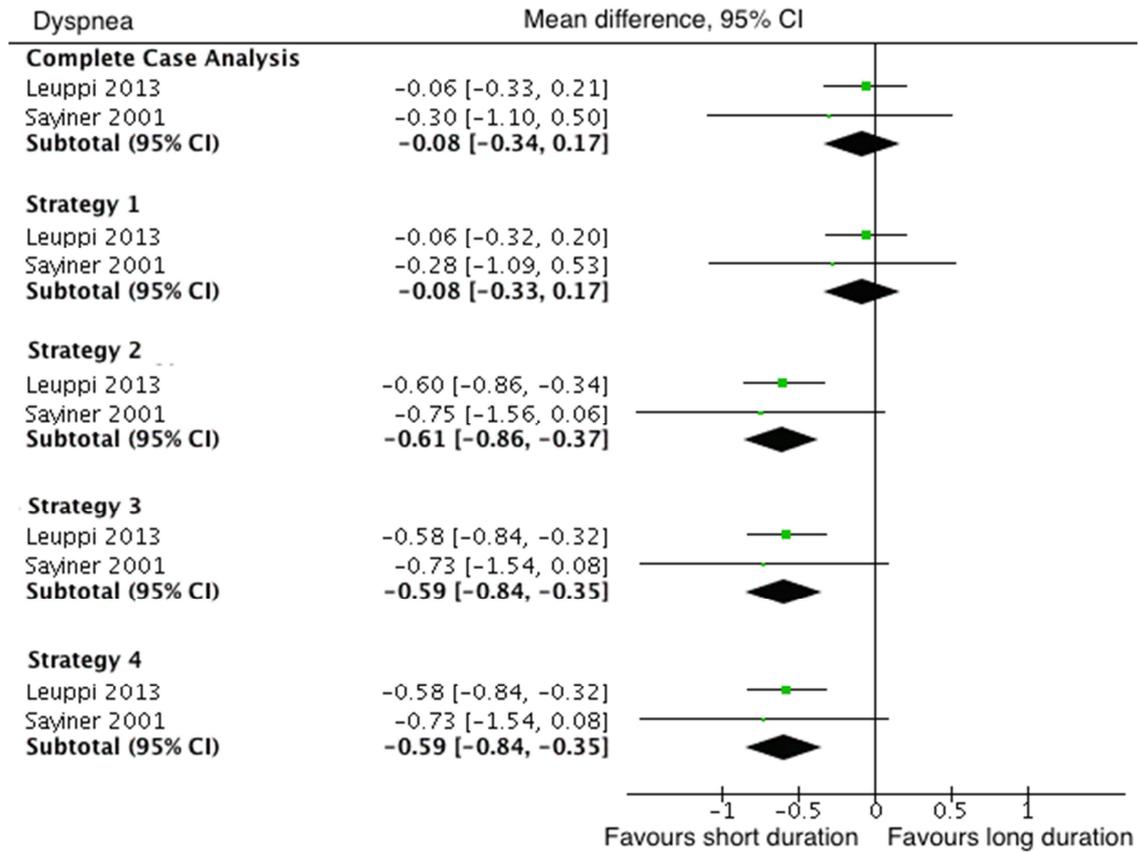


Figure 8. Different durations of corticosteroid therapy for exacerbations of COPD: Dyspnea, complete case analysis and sensitivity analyses using plausible assumptions.

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- When assessing risk of bias associated with participant outcome data across an entire body of evidence, we propose using a complete case analysis for the primary meta-analysis.
- When the results of the primary meta-analysis suggest a statistically significant treatment effect, conduct sensitivity meta-analyses using plausible assumptions to impute events in participants with missing outcome data in each study, and then pool across studies.
- If the results of the primary meta-analysis are robust to the most extreme plausible assumptions, one does not rate down certainty in the evidence for risk of bias due to missing participant outcome data.
- If the results are not robust to plausible assumptions, one would rate down certainty in the evidence for risk of bias.