

## Controversy and Debate: Questionable utility of the relative risk in clinical research: Paper 1: A call for change to practice

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**CONTROVERSY & DEBATE****Controversy and Debate: Questionable utility of the relative risk in clinical research: Paper 1: A call for change to practice**

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**Abstract**

**Background and Objectives:** In clinical trials, the relative risk or risk ratio (RR) is a mainstay of reporting of the effect magnitude for an intervention. The RR is the ratio of the probability of an outcome in an intervention group to its probability in a control group. Thus, the RR provides a measure of change in the likelihood of an event linked to a given intervention. This measure has been widely used because it is today considered a measure with “portability” across varying outcome prevalence, especially when the outcome is rare. It turns out, however, that there is a much more important problem with this ratio, and this paper aims to demonstrate this problem.

**Methods:** We used mathematical derivation to determine if the RR is a measure of effect magnitude alone (i.e., a larger absolute value always indicating a stronger effect) or not. We also used the same derivation to determine its relationship to the prevalence of an outcome. We confirm the derivation results with a follow-up analysis of 140,620 trials scraped from the Cochrane.

**Results:** We demonstrate that the RR varies for reasons other than the magnitude of the effect because it is a ratio of two posterior probabilities, both of which are dependent on baseline prevalence of an outcome. In addition, we demonstrate that the RR shifts toward its null value with increasing outcome prevalence. The shift toward the null happens regardless of the strength of the association between intervention and outcome. The odds ratio (OR), the other commonly used ratio, measures solely the effect magnitude and has no relationship to the prevalence of an outcome in a study nor does it overestimate the RR as is commonly thought.

**Conclusions:** The results demonstrate the need to (1) end the primary use of the RR in clinical trials and meta-analyses as its direct interpretation is not meaningful, (2) replace the RR by the OR, and (3) only use the postintervention risk recalculated from the OR for any expected level of baseline risk in absolute terms for purposes of interpretation such as the number needed to treat. These results will have far-reaching implications such as reducing misleading results from clinical trials and meta-analyses and ushering in a new era in the reporting of such trials or meta-analyses in practice. © 2020 The Authors. Published by Elsevier Inc. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

**Keywords:** Binary effect measure; Relative risk; Odds ratio; Risk difference; Posterior probability; Clinical trial

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### What is new?

#### Key findings

- The relative risk or risk ratio (RR) does not reflect effect magnitude alone but rather is a ratio of two conditional probabilities that vary with outcome prevalence.
- The odds ratio (OR) is a true effect magnitude measure and represents the fold increase in odds of outcome from an unexposed state to an exposed state.
- The risk difference and numbers needed to treat can easily be computed from the OR.

#### What this adds to what was known?

- The reason for the asymmetry of the RR is now clarified.
- The reason why the RR and OR differ and why has now been clarified.
- The utility of the RR as an effect magnitude measure has been questioned, given that it is the ratio of two posterior probabilities, both of which are highly dependent on the prevalence of the outcome in a study.
- The status of the OR as an effect measure has been clarified.

#### What is the implication and what should change now?

- The RR should no longer be used in clinical trials, cohort studies, and meta-analyses.
- The OR is the effect measure of choice in analytic epidemiological studies.
- The risk difference and numbers needed to treat should be derived from the OR.

## 1. Introduction

In clinical trials, the relative risk or risk ratio (RR) is a mainstay of reporting of the effect magnitude for an intervention [1]. The RR is the ratio of the probability of an outcome in an intervention group to the probability of an outcome in a control group; thus, the RR provides an increase or decrease in the likelihood of an event based on some intervention. Despite some concerns [2–4], the RR has been widely used because it is considered a measure with “portability” across varying outcome prevalence, especially when the outcome is rare [3]. The RR is probably the oldest and most used of a variety of measures of association, which have been developed [5] to express in

quantitative terms the relationship between an exposure (e.g., risk factor or intervention) and a binary outcome, but its first use in clinical research is more recent and attributed to Cornfield [6–8].

The RR has also been approximated by the odds ratio (OR), an approximation that has been described much earlier in clinical research [9,10]. The use of the OR to estimate the RR has been thought to be appropriate for studies of rare outcomes; however, the RR and OR are not numerically equivalent when the outcome is common [11], and in the latter situation, the RR may not even have a monotone relationship with the OR [12]. It has also been thought that the OR overestimates the RR and thus may inappropriately affect clinical decision-making or policy development, leading to unintentional errors in the analysis of treatments [13].

By and large, the RR remains more popular today than the OR, especially when reporting clinical trials and meta-analyses of clinical trial data. This is, in part, because of the notion that researchers should preferably choose more interpretable measures of association based on a ratio or difference in risks to minimize confusion and misrepresentation of research [2,14–17]. However, what has been ignored is the fact that the RR is asymmetric [18], and this has led to some uncertainty over its constancy across baseline risks [2,3] and over interpretation and applicability of its results [19]. Today, the debate continues over the merits of the OR vs. the RR and their interpretation [12,20].

In this article, we will show that the RR is not a measure of the magnitude of the intervention–outcome association alone because it has a stronger relationship with prevalence and therefore is not generalizable beyond the baseline risk of the population in which it is computed. More importantly, we will also demonstrate that the ORs accurately reflect the increase or decrease in odds attributed to an exposure/intervention over baseline odds in a control group and thus accurately estimate the effect magnitude, and there is no overestimation of effect magnitude by the OR. We should point out that we will use outcome prevalence and cumulative incidence (in the whole study) synonymously, as the outcome prevalence is equal to the cumulative incidence proportion when we define (as we must) the outcome prevalence at the end of the follow-up period.

## 2. Derivation from first principles

Bayes described the relationship between the posterior probability of an outcome conditional on an exposure based on the unconditional prior probability and an evidence factor. This can be restated in terms of the posterior odds of an outcome ( $D$ ) conditional on an exposure ( $E$ ) based on the population-level prior odds and an evidence factor (likelihood ratio) [21,22]. The latter can be given by the following expression:

$$\frac{P(D|E)}{P(\bar{D}|E)} = \frac{P(E|D)}{P(E|\bar{D})} \times \frac{P(D)}{P(\bar{D})} \quad [1]$$

and we will subsequently use  $\bar{E}$  to denote nonexposure as well as  $\bar{D}$  to denote the absence of the outcome.

The evidence factor or likelihood ratio is a ratio of two exposure probabilities: the outcome group exposure probability ( $\varphi_1$ ) and the no outcome group exposure probability ( $\varphi_0$ ). The ratio  $\varphi_1/\varphi_0$  is called the exposure likelihood ratio but also equals the exposure conditional OR ( $OR_E$ ) and represents the ratio of the exposure conditional odds of outcome to the unconditional odds of outcome in the general population and is given by:

$$OR_E = \frac{P(D|E)}{P(\bar{D}|E)} \bigg/ \frac{P(D)}{P(\bar{D})} = \frac{\varphi_1}{\varphi_0} \quad [2]$$

Similarly, the no-exposure likelihood ratio represents the conditional OR ( $OR_{\bar{E}}$ ) in the nonexposed population. This ratio is thus the nonexposure conditional odds of an outcome to the unconditional odds of the same outcome in the general population and is given by:

$$r_0 = P(D|\bar{E}) = \frac{(1 - \varphi_1)\delta}{(1 - \varphi_0) - \delta(\varphi_1 - \varphi_0)} = \frac{\delta OR_{\bar{E}}}{(\delta[OR_{\bar{E}} - 1] + 1)} \quad [5]$$

$$OR_{\bar{E}} = \frac{1 - \varphi_1}{1 - \varphi_0} \quad [3]$$

These two likelihood-based ORs are different from that commonly computed in a case–control study, where the ratio of odds is that of the retrospective outcome conditional odds of exposure to the retrospective no outcome conditional odds of exposure, and this would be exactly the same (mathematically) as the retrospective exposure conditional odds of outcome to the retrospective no-exposure conditional odds of outcome. This classical OR ( $OR_C$ ) is therefore given by:

$$OR_C = \frac{\varphi_1}{\varphi_0} \bigg/ \frac{(1 - \varphi_1)}{(1 - \varphi_0)} = \frac{OR_E}{OR_{\bar{E}}} = \frac{\varphi_1(1 - \varphi_0)}{\varphi_0(1 - \varphi_1)} \quad [4]$$

and is equivalent to the diagnostic OR in diagnostic studies [23]. Both the  $OR_C$  and  $OR_E$  are independent of prevalence but represent different ORs. The  $OR_C$  represents the ratio of two outcome odds (exposure conditional vs. no exposure conditional), whereas the  $OR_E$  denotes the ratio of two outcome odds (exposure conditional vs. unconditional) and so they only differ in the denominator odds. The  $OR_C$  is therefore the ratio of the two likelihoods (or ORs) and represents the fold increase in odds from the no exposure state to the exposure state. This is easy to see from the following expression:

$$OR_C = \frac{LR_E}{LR_{\bar{E}}} = \frac{OR_E}{OR_{\bar{E}}}$$

In prospective cohort studies, we can compute prospective probabilities of outcome (known as risks) in the exposure group ( $r_1$ ) and in the nonexposure group ( $r_0$ ). The ratio of these risks is the RR popularly used in epidemiology today. However, the retrospective likelihood ratio and the prospective risk ratio are not equal and thus

$$\frac{r_1}{r_0} = \frac{P(D|E)}{P(D|\bar{E})} \neq \frac{\varphi_1}{\varphi_0} = \frac{P(E|D)}{P(E|\bar{D})}$$

Cornfield [6] has shown that the retrospective proportions can be used to compute risks if the prevalence of the disease ( $\delta$ ) in the general population is taken into consideration as follows:

$$r_1 = P(D|E) = \frac{\varphi_1 \delta}{\varphi_1 \delta + \varphi_0(1 - \delta)} = \frac{\delta OR_E}{(\delta[OR_E - 1] + 1)} \quad [5]$$

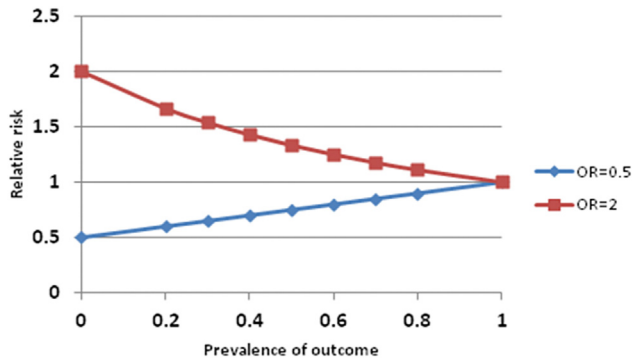
It is quite easy to compute prospective conditional

outcome risks at any value of the population-level prevalence using the  $OR_E$  or the  $OR_{\bar{E}}$  as depicted previously, and it follows that the ratio of expressions [5] and [6] is the RR given by

$$RR = \frac{OR_E(\delta OR_{\bar{E}} - \delta + 1)}{OR_{\bar{E}}(\delta OR_E - \delta + 1)} \quad [7]$$

It is clear therefore from expression [7] that the RR is *dependent* on the prevalence of an outcome and therefore is not “portable” across prevalence levels and therefore only partially reflects the exposure–outcome association. In addition, the RR only approximates the  $OR_C$  when  $RR_{\delta \downarrow 0}$  or  $RR_{\delta(\varphi_1 - \varphi_0) \downarrow 0}$ . In all other cases, the numerical value of the  $OR_C$  will always differ from the RR. This can be easily demonstrated by computing the RR and OR at varying prevalence levels. As shown in Fig. 1, when the OR is held constant and the prevalence of outcome increases, the RR shifts progressively toward the null. If we accept the OR as an effect magnitude measure that quantifies the fold increase in odds of an outcome from the nonexposure state to the exposure state, then as depicted in Fig. 1, the RR does not reflect the exposure–outcome association if outcome prevalence is ignored.

It is quite easy to compute the prospective risk in those exposed at any value of the no-exposure risk ( $r_0$ ) because



**Fig. 1.** Relationship of the relative risk to outcome prevalence when the odds ratio (OR) is held constant.

we would simply need to replace  $OR_E$  with  $OR_C$  and  $\delta$  with  $r_0$  in expression [5] so that

$$r_1 = \frac{r_0 OR_C}{r_0 [OR_C - 1] + 1} \quad [8]$$

and dividing expression [8] by  $r_0$  again gives the risk ratio as follows:

$$RR = \frac{OR_C}{r_0 [OR_C - 1] + 1} \quad [9]$$

This is exactly the expression suggested by Zhang and Yu [24] in 1998, although the use of this expression to generate confidence limits for the RR based on the limits of the OR by substitution has been criticized on the grounds that the proposed confidence interval for the RR would be too narrow presumably because of its failure to account for variability in the baseline risk [25]. This may, however, be a reflection of the RR dependence on prevalence [26], and this is no longer an issue, given that this derivation advocates using the OR and its limits to determine posterior probabilities for a fixed baseline risk of interest from which clinically useful limits for the absolute effect sizes [27,28] are derived. If we fix baseline risk, these limits are then, presumably a function only of the estimated variability in the OR.

Subtracting expression [8] from  $r_0$  gives the risk difference (RD) [27,28] for any baseline risk given by

### Box 1 Key expressions of importance

This box depicts the main relationships that emerge from expressions [9] to [11] where  $r_0$  is the baseline risk and  $OR_C$  is the classical odds ratio. The confidence limits are determined from those of the classical odds ratio and the key expressions of interest are:

$$r_1 = \frac{r_0 OR_C}{r_0 [OR_C - 1] + 1}$$

$$NNT = \frac{r_0 OR_C - r_0 + 1}{r_0 (r_0 - 1) (OR_C - 1)}$$

$$RD = \frac{r_0 (r_0 - 1) (OR_C - 1)}{r_0 OR_C - r_0 + 1} \quad [10]$$

and finally the reciprocal of expression [10] gives the number needed to treat (NNT) [27,28] given by

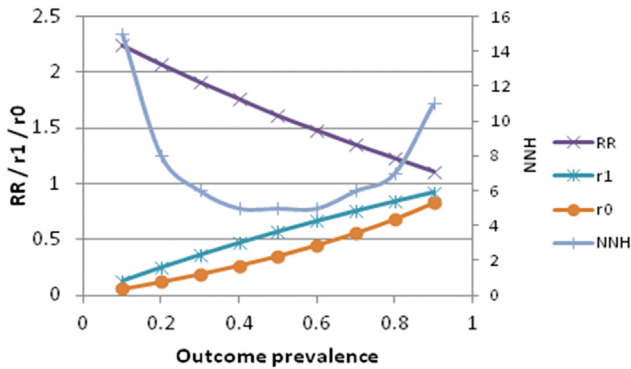
$$NNT = \frac{r_0 OR_C - r_0 + 1}{r_0 (r_0 - 1) (OR_C - 1)} \quad [11]$$

### 3. Implications of the derivation

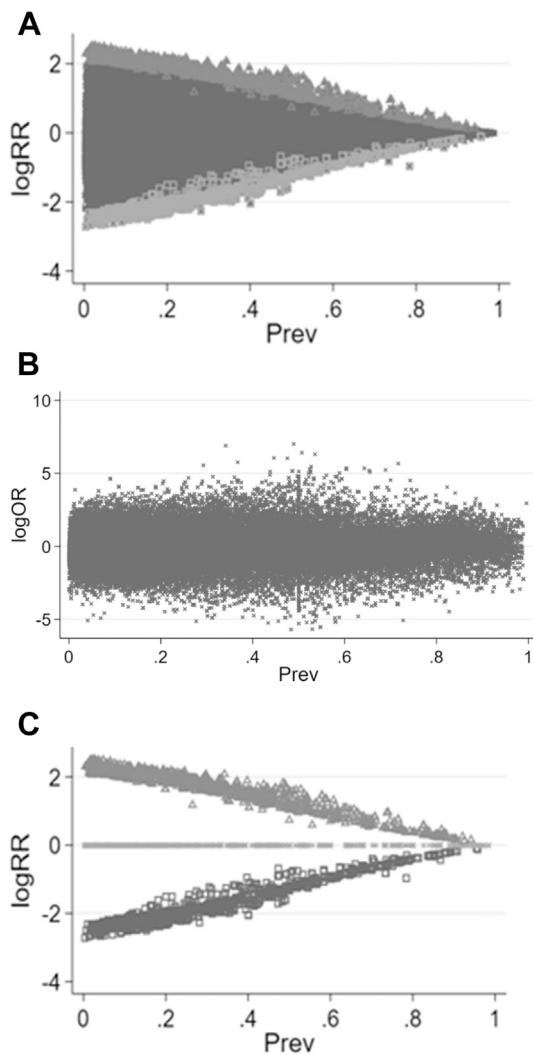
Just as the presence of a positive test result has a diagnostic likelihood associated with it, the presence of an exposure or an intervention also has an outcome likelihood associated with it. With diagnostic tests, this outcome is the actual diagnosis, whereas with exposures and interventions, the outcome may be disease or disease states. Taking Bayes' theorem into consideration, it becomes clear (expression [1]) that the ratio of both likelihoods (likelihood with and without the exposure) equals the ratio of two conditional odds (expression [4]): the exposure conditional odds of outcome to no-exposure conditional odds of the outcome). From any baseline odds of nonexposure, this relationship

**Table 1.** Tabulation of the data depicted in Fig. 2

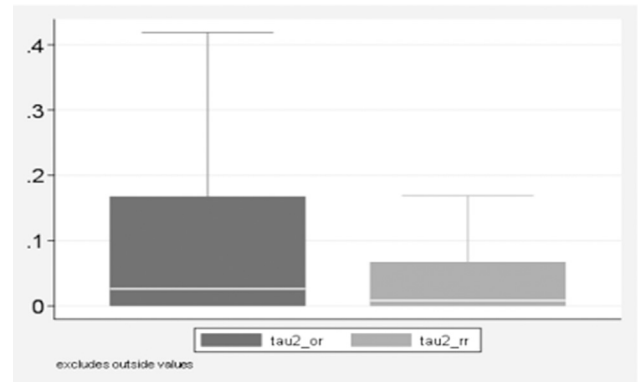
$\delta$	$OR_E$	$OR_{\bar{E}}$	$OR_C$	$RR$	$r_1$	$r_0$
0.1	1.33	0.55	2.42	2.24	0.1285	0.0574
0.2	1.33	0.55	2.42	2.07	0.2492	0.1204
0.3	1.33	0.55	2.42	1.91	0.3626	0.1901
0.4	1.33	0.55	2.42	1.76	0.4695	0.2674
0.5	1.33	0.55	2.42	1.61	0.5704	0.3538
0.6	1.33	0.55	2.42	1.48	0.6657	0.4510
0.7	1.33	0.55	2.42	1.35	0.7560	0.5610
0.8	1.33	0.55	2.42	1.23	0.8415	0.6866
0.9	1.33	0.55	2.42	1.11	0.9228	0.8313



**Fig. 2.** Relationship of the relative risk (RR), exposure risk ( $r_1$ ), no exposure risk ( $r_0$ ), and number needed to harm (NNH) to outcome prevalence for the data in Table 1.



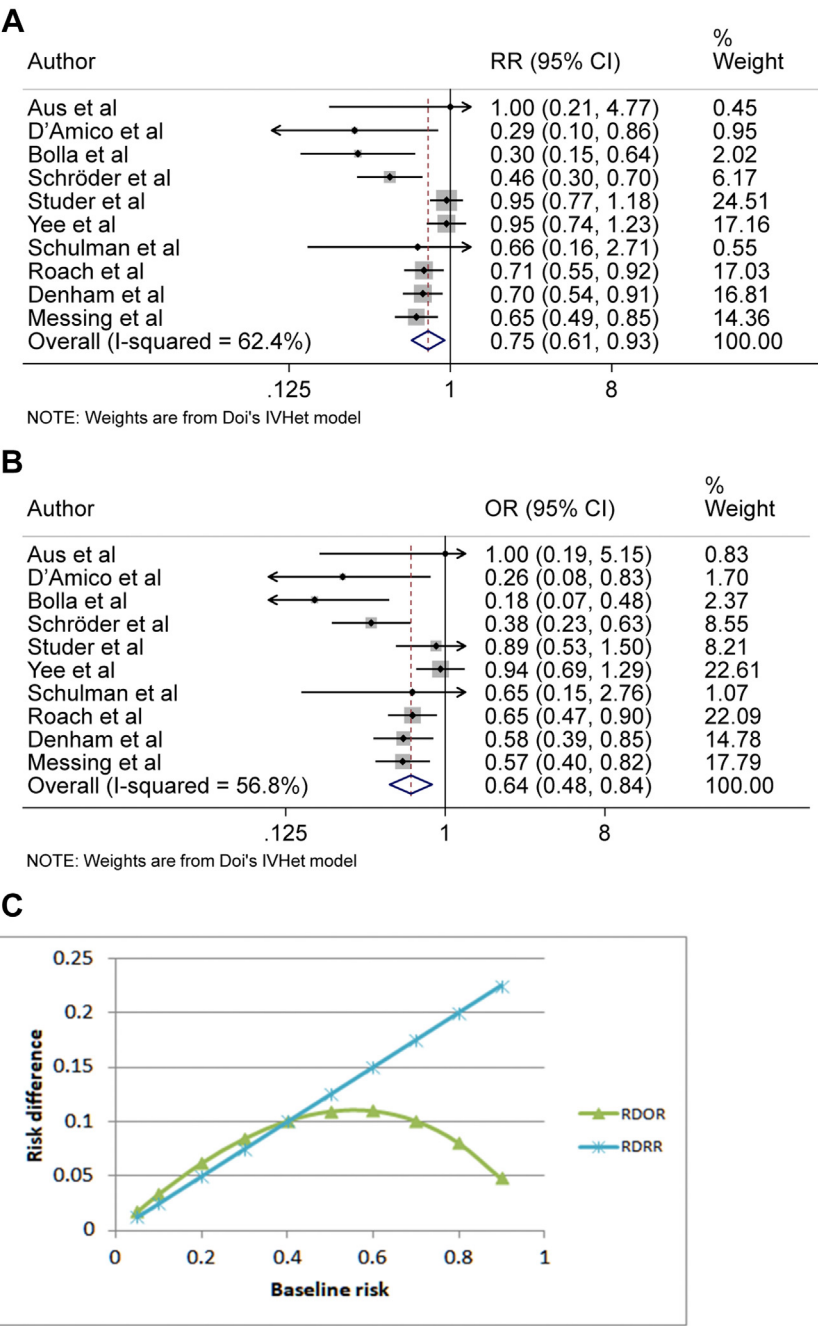
**Fig. 3.** Relationship between the logRR (panel A), logOR (panel B) and outcome prevalence across all 140,620 trials. The trials with fixed ORs are depicted in panel C with a hollow square (percentile 2; OR range 0.06 to 0.1), with a X (percentile 55; OR of 1) and with a hollow triangle (percentile 99; OR range 8.3 to 13.2).



**Fig. 4.** The RR-based meta-analyses (right box plot) were less heterogeneous than the OR based ones (left box plot). OR, odds ratio; RR, relative risk.

can be used to generate the odds with exposure as well as the conditional risks and their ratio, RD, and the NNT or number needed to harm (NNH). Box 1 depicts the important relationships that emerge based on the derivation mentioned previously. The expression for the RR is not included in Box 1, and the reason this is left out is that exposure–outcome association magnitude cannot be ascertained directly with the RR because it actually reflects the ratio of outcome probability in the presence of exposure (akin to the positive predictive value [PPV]) to outcome probability without exposure (akin to 1-negative predictive value [1-NPV]), and thus, the  $RR = PPV/(1-NPV)$  [29], and both the PPV and 1-NPV increase with outcome prevalence in a study. Thus, the RR represents a ratio of two posterior probabilities conditional on exposure and nonexposure, whereas the OR is a true measure of effect magnitude because it is a measure of the fold increase in odds of the outcome from the no exposure/no intervention state to the exposure/intervention state and is constant for any given exposure/intervention. Table 1 and Fig. 2 depict this issue using hypothetical data regarding an exposure (smoking 10 or more cigarettes per day). The hypothetical data are based on the premise that 77% of lung cancer subjects smoked that much, whereas only 58% of a group of non-lung cancer subjects smoked that much. As baseline population prevalence of cancer varies from 10% to 90% and the various likelihoods ( $OR_E$  and  $OR_{\bar{E}}$ ) are held constant, the two risks and their ratio (RR) vary. The reason why this happens is clearly depicted in Table 1 and Fig. 2, where the NNH and RR are highly dependent on the prevalence of the outcome as mathematically demonstrated previously. The OR does not have this issue because it also is a likelihood ratio and therefore is invariant with the prevalence of disease/outcome. The fact that it is a likelihood ratio also explains the observation by Hoppe et al. [30] that the OR can also be interpreted in terms of a conditional RR, given discordant pairs from unmatched data collected pairwise. In contrast, expressing both posterior probabilities as a ratio (i.e., the conventional RR) is meaningless. The absolute change from nonexposure to exposure is what is meaningful





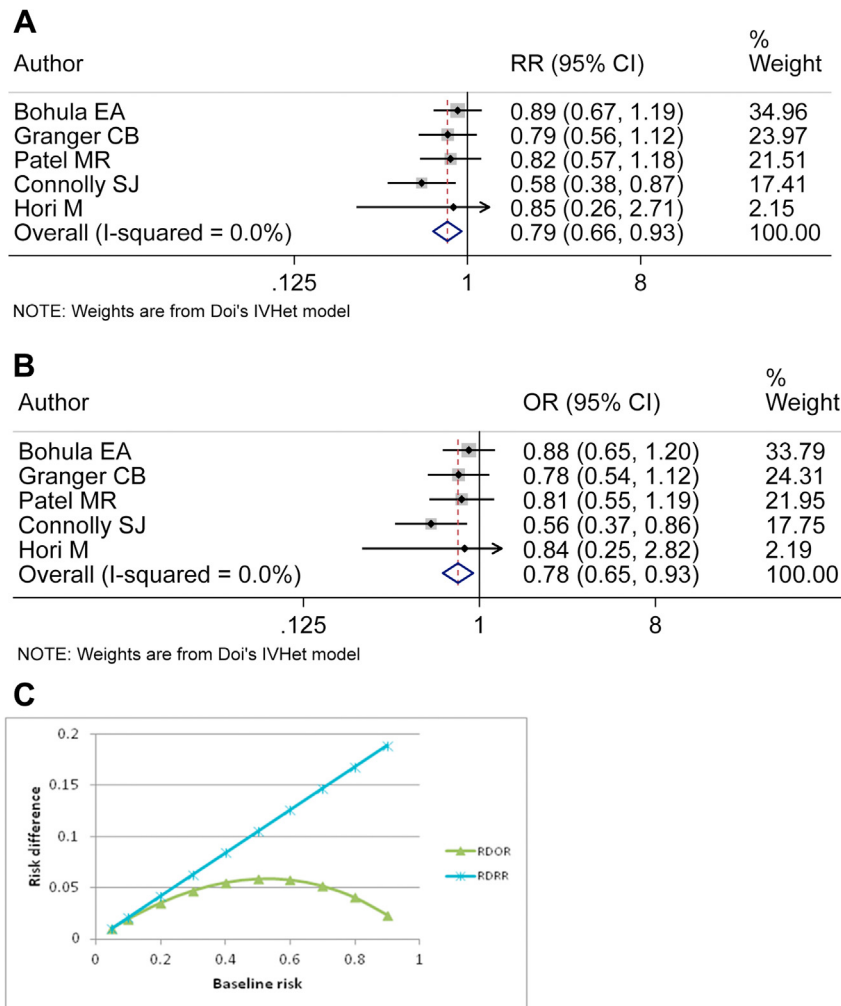
**Fig. 5.** Meta-analysis of prostate cancer–specific mortality associated with androgen deprivation therapy among patients with prostate cancer. The (A) RR and (B) OR differ because mortality across studies ranges between 2% and 59%. There is a divergence in risk difference (C) when the latter is computed from either the OR or the RR. (Note: OR, odds ratio; RR, relative risk).

and can be expressed as a NNH or NNT and can be computed from the OR for any specific baseline nonexposure risk through the relationships depicted in [Box 1](#).

**4. Analysis of 140,620 trials scraped from Cochrane**

Data from individual studies of meta-analyses published in the Cochrane Database of Systematic Reviews from 2003 (Issue 1) to 2018 (Issue 5) were extracted using the

R package “RCurl.” The R code has been provided in a previous study, which used this data set to compare tests for publication bias [31]. A total of 181,278 trials used in 18,562 meta-analyses were scraped from Cochrane. We dropped meta-analyses containing trials with zero events in both arms. We also dropped studies with baseline or intervention risks exactly equal to zero or one and dropped meta-analyses with less than five studies (in this sequence). There were 140,620 trials left for analysis across 14,960 meta-analyses. The RR, OR, outcome prevalence, and



**Fig. 6.** Meta-analysis of stroke or systemic embolism after high dose non-vitamin K oral anticoagulants vs vitamin K antagonists. The (A) RR and (B) OR are similar because outcome incidence across studies ranges between 4% and 6%. There is a divergence in risk difference (C) when the latter is computed from either the OR or the RR. (Note: OR, odds ratio; RR, relative risk).

baseline risk in the control group were computed for each of these trials (regardless of meta-analysis they belonged to). The ORs were found to have no association with prevalence, and all the expressions derived previously (and in Box 1) were confirmed to be numerically equivalent to the directly computed RR, RD, or NNT/NNH. The relationship between the RR and the prevalence described mathematically previously was confirmed and is depicted in Fig. 3. As the RR is a ratio of two conditional probabilities, it loses meaning, given that the two conditional probabilities increase with prevalence, and when the association between exposure and outcome is fixed (by generating percentiles of the logOR and analyzing by percentile), the RR is just a linear function of prevalence and nothing more (Fig. 3C). A similar relationship is seen when prevalence is fixed by percentile and depicted in Supplementary Fig. S1.

Given this finding, pooled effects from meta-analyses using the RR effect measure will tend to be increasingly misleading, as prevalence of the outcome increases or

varies across studies (in meta-analyses) and will also be expected to have decreasing heterogeneity with increasing prevalence. This was demonstrated by computing these meta-analyses using the fixed effect model in Stata (Stata-Corp, College Station, TX, USA), and the results show much less heterogeneity (between studies variance, tau<sup>2</sup>) when pooling using the RR compared with when pooling using the OR, and this was expected, given the range limitation of the RR as prevalence increased (Fig. 4). In keeping with our observation, the use of the RR in meta-analysis has recently been flagged as a source of bias in RR-based meta-analyses [32].

#### 4. Examples from the literature

In a meta-analysis of prostate cancer-specific mortality associated with androgen deprivation therapy among patients with prostate cancer [33], the pooled OR = 0.64



and  $RR = 0.75$  reported were dissimilar (Fig. 5) because mortality varied across studies (2–59%). The implications are also different for when baseline mortality risk varies for those without androgen deprivation therapy. For example, given a hypothetical baseline mortality risk of 10%, this would lead to different values for the postintervention risk difference, and the NNT would then be 58 (OR) vs. 80 (RR) using the OR or the RR, respectively. Of interest here is that Fagan's nomogram can also be used to go from control to postintervention probability using the OR as the likelihood ratio.

In another meta-analysis of stroke or systemic embolism after high dose non-vitamin K oral anticoagulants vs. vitamin K antagonists [34], the authors report the RR for stroke or systemic embolism to be 0.79 (Fig. 6). The meta-analysis using the OR returned numerically similar results because outcome incidence was similar across studies (4–6%). However, the interpretation of both measures differ. Using the OR, assuming varying baseline incidence of stroke or systemic embolism in the vitamin K antagonists group, we get varying results for the RD across the use of the RR or the OR (Fig. 6C). The RR, therefore, gives inaccurate risk information regardless of whether it has or has not got a numerical similarity to the OR.

## 6. Conclusion

In this article, we discuss only two relative measures (OR and RR) and attempt to explain why one of them seems problematic, and thus, by default, this leaves us with only one moving forward. Although many effect measures exist, the differences in objectives for the different measures are not raised in this article, as we focus solely on the debate between OR and RR, and demonstrate that all information previously derived from the RR can just as easily be derived from the OR. Of greater concern is that the RR may not be a valid measure of effect. The basic concepts underpinning this study are all well-established, but what this article adds is that what we think is being measured is not actually what is being measured, and this lends itself to conclusions that are not true.

The main thesis of this article is that RR depends on prevalence more so than on the strength of the exposure–outcome association that it is supposed to reflect. Thus, if the association is unchanged and we modify prevalence, then the relative risk changes. If the strength of the association is measured independently of the RR and kept constant, then we can show that the RR is a linear function of prevalence. We can therefore no longer accept the commonly argued for view that the relative risk is easier to understand. Once we realize that the RR depends more on prevalence than the exposure–outcome association, its interpretation becomes much more difficult to comprehend than the OR.

It is well known that, for common events, large values of the risk ratio are impossible, and this should have rung the alarm bells much earlier regarding whether the RR is more a measure of prevalence than a measure of effect. However, this was not the main focus of the derivation outlined above, and the latter was aimed at demonstrating why the OR is a true measure of effect against which the RR can be compared. The derivations relating to the OR in this article relate primarily to the OR and then are linked to the relative risk through the computation of risk. The derivations do not require the assumption that the probability of exposure given outcome or the probability of exposure given no outcome are constants but rather that they are independent of outcome prevalence. This is logical because they are derived from the outcome or no outcome groups separately. Although test principles are applied in the derivation, a test being a consequence of the outcome or an exposure being a cause of the outcome is not really important in this context because the probabilities are assessed at one point in time—in nondiagnostic studies, this would be at the end of follow-up.

Clinical research has a substantial need for absolute measures, and either the OR or RR can be used to compute these as we show in this article. However, the choice of binary effect measure in epidemiologic studies precedes the computation of such absolute effects. Creating a measure of impact is usually done by combining a relative measure with baseline risk information. However, this can only be done when the relative measure has portability across different risk groups. This article demonstrates this lack of portability with the RR, and hence, both the direct interpretation and the translation to absolute measures of impact are flawed.

It is a common perception that consistency of an effect measure in meta-analysis means that it is the effect measure of choice. This again is a misconception because if the RR does not measure effect magnitude and simply reflects the prevalence of the outcome in the study, consistency is no longer meaningful. Consistency increases with the RR as prevalence increases simply because the RRs become more equal (as well as lose meaning as a measure of effect magnitude). It may be okay to meta-analyse studies with similar prevalence (although if the prevalence is high, interpretation is still questionable), but if this differs across studies (see the example), it makes little sense to meta-analyse such studies, as the RRs cannot be interpreted as similar even if they are fortuitously consistent.

We reiterate that the RR does not fully reflect the magnitude of the effect in clinical trials. Rather, it reflects more of the baseline prevalence of an outcome, shifting toward 1 as prevalence increases. It is also a ratio of two conditional probabilities, making its interpretation questionable. On the other hand, the OR is a likelihood ratio whose magnitude reflects the fold increase in odds from that in the baseline group to that in the intervention group and reflects the magnitude of the intervention effect independent of

prevalence. Interpretation of the OR is similar to that of the likelihood ratio in diagnostic studies. The OR is expected to be specific to any intervention and thus should be the binary effect measure in randomized trials, and meta-analyses of such trials and the RD and NNT should preferably be derived from the OR and not the RR. [Supplementary Material \(S2\)](#) What this article raises about the RR dependence on prevalence should also not be conflated with the well-known fact in epidemiology that the OR approximates the RR when prevalence is small. The latter is about numerical equivalence, thus rendering the OR interpretable as an RR. This has never been previously viewed as a problem inherent to the RR, which is what this study aims to explain. Therefore, although the RR and OR coincide numerically over a narrow range below baseline risks of 20–30%, this is no justification to continue to use this ratio. The risk relativism as it is currently viewed is an illusion.

Finally, we should point out that the basics used in this article reflect well-known material. What we are arguing for is a major change in the status quo regarding interpretation and usage based on these very same basic principles. Although we appreciate the fact that some debates are put out there to stimulate thought and advance understanding, we are also seriously concerned about this issue because we believe the evidence we provide in support of change is compelling.

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## Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jclinepi.2020.08.019>.

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