As described in an earlier EBM note (1) and in our glossary, this journal reports the results of individual randomised trials in terms of relative risk reductions (RRRs), calculated by dividing the absolute difference in event rates between the control (control event rate [CER]) and experimental (experimental event rate [EER]) patients by the event rate for the controls: (CER – EER)/CER = RRR. From these same values, we also report the number of patients that would need to be treated (NNT) to prevent 1 additional event—1/(CER – EER)—or by its alternative calculation—1/(RRR x CER). Thus, in the example shown in Table 1, the RRR is 89% and the NNT is 4 (2).

However, we also report the results of overviews of several randomised trials, and these results appear not as RRRs but as relative odds, or odds ratios (ORs). There are reasons for this variation (although, as it happens, arguably no longer very good ones!). We will explain ORs, point out their properties (many of which interfere with their clinical application), and provide you with some practical help in applying them to individual patients.

When used to summarise an overview, an OR describes the odds of an experimental patient having an adverse event relative to a control patient. We can calculate the odds of a patient having an event by dividing the number of patients who have the event by the number of patients who do not. Hence, for the control group in Table 1, the odds of a patient having the event were c/d = 9/21 = 0.43, which compares to a risk of c/(c + d) = 9/30 = 0.30. If we mistakenly interpret odds as if they were risks, we will exaggerate the latter, especially with events that are more common.

The OR is calculated by dividing the odds in the experimental group by the odds in the control group—(a/b)/(c/d)—or equivalently through the “cross-products” calculation shown below Table 1—ad/bc. From this definition, it follows that efficacious treatments generate ORs < 1, which is analogous to the relative risk (RR) for the adverse event (EER/CER) being < 1. (We usually prefer to think in terms of RRRs, which are equivalent to 1 – RR, but for ease of comparison with ORs, please bear with us and think in terms of RRs.) How did we get into this confusing situation of using ORs in the first place? The OR had its origins in case-control studies of drug side effects and of harmful agents and exposures, such as cigarette smoking. In these case-control studies, it is not possible to estimate RRs directly because the prevalence of the adverse outcome (required for calculating the RR) is not usually known. You can, however, calculate the OR in these situations, either by comparing the odds of incurring an adverse event in the exposed group and the control group (i.e., [a/b]/[c/d] = ad/bc) or by comparing the odds of exposure in the event and nonevent groups (i.e., [a/c]/[b/d] = ad/bc); both routes lead to the same answer, which will be > 1 when the exposure is harmful. Hence, the OR can be estimated when the prevalence of the events is unknown, as in most case-control studies. Moreover, because case-control studies typically are used for the study of rare events, the distortion of risk produced by interpreting ORs as if they were RRs is negligible (if necessary, refresh your memory by rereading the 3rd paragraph in this note).

When ORs came into use, several powerful and informative statistical methods were developed (by persons such as Nathan Mantel and William Haenszel) for use in analysing subgroups of patients and combining them (even when the latter were unbalanced for confounding factors) into a single overall estimate (3). Later, when scientists began to do overviews of multiple randomised trials and were seeking a statistical method for combining their results, the analogy with combining subgroups in case-control studies was recognised.

### Table 1. Trimethoprim-sulfamethoxazole prophylaxis in cirrhosis*

<table>
<thead>
<tr>
<th>Treatment group</th>
<th>Adverse event (infectious complications)</th>
<th>Totals</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Occurs</td>
<td>Does not occur</td>
</tr>
<tr>
<td>Experimental (prophylaxis)</td>
<td>1</td>
<td>a</td>
</tr>
<tr>
<td>Control (no prophylaxis)</td>
<td>9</td>
<td>c</td>
</tr>
<tr>
<td>Totals</td>
<td>10</td>
<td>a+c</td>
</tr>
</tbody>
</table>

*From reference 2.

Control event rate = CER = c/(c+d) = 0.30; experimental event rate = EER = a/(a+b) = 0.033
Control event odds = c/d = 0.43; experimental event odds = a/b = 0.034
Relative risk reduction = RRR = (CER – EER)/CER = 89%
Number needed to treat = NNT = 1/(CER – EER) = 4, also = 1/(RRR x CER) = 4
Relative risk = EER/CER = 0.11, also = 1 – RR = 0.11
Relative odds = odds ratio = OR = (a/b)/(c/d) = ad/bc = 0.08
and the Mantel-Haenszel method was adapted to this new use (soon joined by a computationally simpler method developed by Richard Peto [4] that provides good approximations to the OR when treatment effects are small and the trials being combined are large and balanced [5]). For these reasons, ORs are now commonly used in the analysis and reporting of overviews of randomised trials that have binary outcomes.

ORs, however, have 5 properties that interfere with their clinical application. First, because very few clinicians are facile at dealing with odds and relative odds, ORs are not useful in their original form at the bedside or in the examining room. Second, in many trials, ORs are not even similar to RRs: In many fields, controlled trials tend to study common adverse events, and it is in these situations that the approximation of the OR to the RR breaks down. Treating an OR as if it were an accurate estimate of the RR will overestimate both the likely benefits and harms of treatment (6), and this distortion becomes greater as the disease being treated becomes more severe and CERs increase.

Third, and as a result of the foregoing, ORs cannot be used in the same simple way as RRs to calculate the corresponding NNTs for the treatments of interest. To extrapolate results from trials that have different patient expected event rates (PEERs), clinicians need to do separate and complicated calculations of the NNT for each PEER. Although we expect the NNT to decrease as the PEER rises for a treatment with a fixed relative effect, even this is not true for ORs! Looking down a column in Table 2 will show you that, for a fixed OR, the NNT initially decreases as the PEER rises (as expected), but it increases again when the PEER is above 0.5. This counterintuitive result occurs because the difference between the RR and the OR accelerates as event rates rise.

Fourth, when treatments generate a constant RRR for different CERs (e.g., antihypertensive drugs generate the same RRR for stroke among patients with both severe and mild hypertension), their ORs cannot be constant across these CERs (and vice versa). Finally, when clinicians draw up “league tables” of therapeutic efficacy, the order of treatments based on their ORs when the diseases and disorders in the table are of different severity and have different CERs.

Help is on the way (but not quite here yet). Prospects are very good that meta-analyses do not have to be done by using ORs. Statistical methods...
ods for combining both relative risks and absolute risk differences across trials are available (7), although some concern exists that they are not appropriate for all circumstances. Validation work is under way to outline the situations where they can be widely adopted for combining randomised trials into systematic reviews. As soon as these clinically friendlier alternatives are used in reporting the results of overviews, they will appear in Evidence-Based Medicine. In the meantime, we will be adding Table 2 to our glossary, which permits our readers to identify NNTs for a range of ORs and PEERs. The intersection of the OR closest to that reported in the overview with the PEER that best represents the reader’s patient will identify the corresponding NNT. For readers who want to do the full calculations, the formula appears below Table 2.

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References