The Results of Direct and Indirect Treatment Comparisons in Meta-Analysis of Randomized Controlled Trials

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ABSTRACT. When little or no data directly comparing two treatments are available, investigators often rely on indirect comparisons from studies testing the treatments against a control or placebo. One approach to indirect comparison is to pool findings from the active treatment arms of the original controlled trials. This approach offers no advantage over a comparison of observational study data and is prone to bias.

We present an alternative model that evaluates the differences between treatment and placebo in two sets of clinical trials, and preserves the randomization of the originally assigned patient groups. We apply the method to data on sulphamethoxazole–trimethoprim or dapsone/pyrimethamine as prophylaxis against Pneumocystis carinii in HIV infected patients. The indirect comparison showed substantial increased benefit from the former (odds ratio 0.37, 95% CI 0.21 to 0.65); while direct comparisons from randomized trials suggest a much smaller difference (risk ratio 0.64, 95% CI 0.45 to 0.90; p-value for difference of effect = 0.11).

Direct comparisons of treatments should be sought. When direct comparisons are unavailable, indirect comparison meta-analysis should evaluate the magnitude of treatment effects across studies, recognizing the limited strength of inference. J CLIN EPIDEMIOL 50;6:683-691, 1997. © 1997 Elsevier Science Inc.

KEY WORDS: Meta-analysis, methodology, clinical epidemiology, outcome, HIV infection, Pneumocystis carinii pneumonia

INTRODUCTION
Physicians in almost every field of medicine face an increasing number of treatment options. Deciding between these treatments is often difficult. For instance, two drugs may have demonstrated effectiveness in comparison to placebo or standard treatment in well-executed randomized trials, but direct comparisons of effectiveness between these agents may be unavailable.

In recent years meta-analysis has become a widespread method to improve clinical decision-making by simultaneously considering the results of multiple randomized trials. Meta-analysis provides a potential solution to the problem of deciding between treatments that have not been directly compared. For example, Felson et al. [1] conducted a meta-analysis examining the relative effectiveness and toxicity of second-line drugs in rheumatoid arthritis. Because few of the drugs of interest had been subject to direct comparisons, the investigators chose to compare patients in different trials given competing second-line agents, rather than comparing them with the placebo-treated control subjects in their own trials. Although all data in this meta-analysis came from randomized controlled trials, the power of randomization is lost and the data are reduced to the equivalent of those derived from contemporaneous or historical cohort studies. This comparison is no stronger than one obtained from an observational study in which patients are drawn from separate populations, with the likelihood that differences in prognosis unrelated to treatment will bias the comparison of effectiveness [2].

Indirect comparisons can also form the basis of models used by health economists for their cost-effectiveness analyses. In the absence of direct comparison of enoxaparin or warfarin for the prophylaxis of post-surgical deep vein thrombosis, O'Brien et al. [3] combined data from the treatment arms of ten randomized trials that compared either enoxaparin or warfarin versus placebo. Because, once again, the power of randomization is lost, and the groups are likely to differ in their prognosis, it is unlikely that an unbiased comparison will result from this strategy.

When direct comparisons are unavailable, is there any alternative strategy for pooling data that is less susceptible to bias? Conceptually, we could examine the magnitude of
the treatment effect in studies of different treatments and compare those treatment effects. With this approach it is possible that even if both control and treatment groups differ in their baseline characteristics, we may obtain an unbiased estimate of treatment effect. The only requirement is that the magnitude of the treatment effect is constant across differences in the populations' baseline characteristics.

In this paper, we present a model for making indirect comparisons of the magnitude of treatment effects that preserves the randomization of the originally assigned patient groups. We illustrate this model with an example from a meta-analysis of randomized controlled trials that compares two experimental prophylactic regimens against the standard prophylaxis for the prevention of Pneumocystis carinii pneumonia in patients with HIV infection. We contrast the results derived from analyses that compare results of treatment groups from different trials, the results from randomized controlled trials investigating the two prophylactic regimens of interest by direct comparisons, and our model of indirect comparisons.

A Model for the Indirect Comparison of Proportional Data

In the discussion that follows, we will focus on the odds ratio as our measure of treatment effect. The method could be equally applied to estimates of relative risk. The appendix presents more detailed derivations of the formulas while the following text presents the ideas conceptually.

In meta-analysis the overall measure of association is typically taken as the weighted average of the individual studies with weights being the inverse of the variance for each study. Let us consider a situation where g studies have compared treatment A to standard treatment B and h studies have compared treatment C to standard treatment B. Our interest is in obtaining an indirect estimate of the association of A versus C. To obtain an indirect estimate of the association A versus C from the paired comparisons of A versus B and of C versus B, first an overall measure of variation can be taken as the sum of the total chi-squared values from the paired comparisons with g + h degrees of freedom. A summary odds ratio of the indirect comparison can then be computed by taking the ratio of the log odds ratio from studies comparing A versus B and from studies comparing C versus B.

The estimate we derive from this approach will be unbiased in large samples if there is no interaction between covariates defining subgroups of patients (reflected, for instance, in different inclusion criteria in different studies) and the magnitude of the treatment effect. The appendix provides a proof of unbiasedness of our estimate if no such interaction is present. If an interaction is present, then the pooling of data across studies is questionable, even for direct comparisons.

This model then allows application of standard methods whereby we express the association of a treatment effect from a number of studies that each estimate a level of association between an intervention and an outcome by a chi-squared distribution. If the value of chi-squared is large we may conclude that there is association between treatment and outcome somewhere within the studies. However, we would not know whether the association was consistent across all studies or whether it varied from one group of studies to another. We can elucidate this issue by partitioning the chi-squared into two components, a chi-squared which assesses the degree of heterogeneity and a chi-squared that assesses the significance of the average degree of association.

Application of the Model and Comparison with Other Approaches

We tested our model in a meta-analysis of randomized controlled trials that compare two experimental (trimethoprim–sulphamethoxazole and dapsone/pyrimethamine) and one standard regimen (aerosolized pentamidine) for primary and secondary prevention of Pneumocystis carinii pneumonia in HIV infection. In a systematic review of the literature we identified all randomized controlled trials comparing either trimethoprim–sulphamethoxazole dapsone/pyrimethamine with the standard treatment with aerosolized pentamidine. In addition, we identified all trials providing a direct estimate of the relative effectiveness by comparing trimethoprim–sulphamethoxazole with dapsone or dapsone/pyrimethamine. Details of search strategies, inclusion criteria and the description of included trials are provided in an other publication [4]. For the purpose of this study we report only on the single outcome of Pneumocystis carinii pneumonia.

We identified 22 trials. Nine trials compared trimethoprim–sulphamethoxazole with aerosolized pentamidine [15–13]. Two trials compared dapsone/pyrimethamine [14,15] and three trials dapsone [16–18] with pentamidine. Four trials compared trimethoprim–sulphamethoxazole with dapsone/pyrimethamine [19–22]. Four trials included three treatment arms e.g., one trial compared dapsone [23] and three trials compared dapsone/pyrimethamine [24–26] with trimethoprim–sulphamethoxazole and aerosolized pentamidine. These four trials were only used for the direct comparison of trimethoprim–sulphamethoxazole versus dapsone/pyrimethamine. In these 22 trials a total of 1484 patients had been treated with trimethoprim–sulphamethoxazole, 1547 patients with dapsone or dapsone/pyrimethamine, and 1837 patients with aerosolized pentamidine. We combined nine trials for the comparison of trimethoprim–sulphamethoxazole and aerosolized pentamidine, five trials for the comparison of dapsone/pyrimethamine and aerosolized pentamidine, and eight trials for the direct comparison of dapsone/pyrimethamine and trimethoprim–sulphamethoxazole. In Table 1 we show important baseline characteris-
### TABLE 1. Odds ratios and 95% confidence interval in randomized controlled trials of indirect comparison with either trimethoprim-sulfamethoxazole or dapsone/pyrimethamine compared to aerosolized pentamidine for prevention of *Pneumocystis carinii* pneumonia in HIV-infected subjects

<table>
<thead>
<tr>
<th>Trials: author, year of publication [Reference]</th>
<th>Odds ratio (95% CI)</th>
<th>No. of Ppc and subjects</th>
<th>Mean follow-up (person-years)</th>
<th>Mean CD4 cells (mm³)</th>
<th>Patients with AIDS n (%)</th>
<th>Antiretroviral therapy n (%)</th>
<th>Study quality score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Comparing TMP-SMX with AP</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rozenbaum 1991 [12]</td>
<td>0.30 (0.01–7.67)</td>
<td>29/152</td>
<td>21.7</td>
<td>124</td>
<td>NA</td>
<td>29 (100)</td>
<td>0.47</td>
</tr>
<tr>
<td>Hardy 1992 [5]</td>
<td>0.34 (0.18–0.66)</td>
<td>14/154</td>
<td>202.4</td>
<td>62</td>
<td>154 (100)</td>
<td>139 (90)</td>
<td>0.68</td>
</tr>
<tr>
<td>Schneider 1992 [6]</td>
<td>0.04 (0.00–0.64)</td>
<td>6/71</td>
<td>56.0</td>
<td>90</td>
<td>53 (75)</td>
<td>39 (55)</td>
<td>0.71</td>
</tr>
<tr>
<td>Smith 1992 [11]</td>
<td>0.45 (0.11–1.87)</td>
<td>3/27</td>
<td>49.5</td>
<td>39</td>
<td>27 (100)</td>
<td>22 (76)</td>
<td>0.48</td>
</tr>
<tr>
<td>Michelet 1993 [9]</td>
<td>0.33 (0.05–2.16)</td>
<td>1/53</td>
<td>105.6</td>
<td>159</td>
<td>NA</td>
<td>51 (96)</td>
<td>0.35</td>
</tr>
<tr>
<td>May 1994 [7]</td>
<td>0.43 (0.09–1.98)</td>
<td>2/108</td>
<td>112.7</td>
<td>200</td>
<td>24 (22)</td>
<td>73 (68)</td>
<td>0.61</td>
</tr>
<tr>
<td>Stellini 1994 [10]</td>
<td>0.16 (0.01–3.56)</td>
<td>2/23</td>
<td>35.9</td>
<td>137</td>
<td>2 (8)</td>
<td>18 (69)</td>
<td>0.44</td>
</tr>
<tr>
<td>Nielsen 1995 [8]</td>
<td>0.15 (0.03–0.90)</td>
<td>1/47</td>
<td>66.8</td>
<td>59</td>
<td>47 (100)</td>
<td>45 (96)</td>
<td>0.59</td>
</tr>
<tr>
<td>Rizzardi 1995 [13]</td>
<td>0.89 (0.28–2.88)</td>
<td>5/95</td>
<td>175.5</td>
<td>128</td>
<td>10 (11)</td>
<td>90 (95)</td>
<td>0.70</td>
</tr>
<tr>
<td>Trials comparing D/P or D with AP</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slavin 1992 [16]</td>
<td>1.04 (0.37–2.89)</td>
<td>9/50</td>
<td>49.7</td>
<td>128</td>
<td>16 (32)</td>
<td>N.A.</td>
<td>0.56</td>
</tr>
<tr>
<td>Girard 1993 [14]</td>
<td>1.02 (0.42–2.46)</td>
<td>10/173</td>
<td>238.3</td>
<td>112</td>
<td>115 (67)</td>
<td>162 (94)</td>
<td>0.73</td>
</tr>
<tr>
<td>Torres 1993 [17]</td>
<td>1.23 (0.58–2.60)</td>
<td>15/126</td>
<td>120.0</td>
<td>192</td>
<td>71 (56)</td>
<td>109 (72)</td>
<td>0.73</td>
</tr>
<tr>
<td>Opravil 1995 [15]</td>
<td>0.76 (0.35–1.61)</td>
<td>1/29</td>
<td>342.8</td>
<td>116</td>
<td>52 (18)</td>
<td>262 (90)</td>
<td>0.78</td>
</tr>
<tr>
<td>Salmon 1995 [18]</td>
<td>0.46 (0.16–1.29)</td>
<td>5/92</td>
<td>96.0</td>
<td>57</td>
<td>93 (100)</td>
<td>46 (50)</td>
<td>0.71</td>
</tr>
<tr>
<td>Comparing TMP-SMX with D/P or D and AP</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Antinori 1992 [24]</td>
<td>0.13 (0.02–0.76)</td>
<td>1/66</td>
<td>49.7</td>
<td>107</td>
<td>17 (26)</td>
<td>55 (83)</td>
<td>0.45</td>
</tr>
<tr>
<td>Mallozas 1992 [25]</td>
<td>0.43 (0.12–1.53)</td>
<td>3/107</td>
<td>100.0</td>
<td>160</td>
<td>45 (42)</td>
<td>104 (97)</td>
<td>0.61</td>
</tr>
<tr>
<td>Tocchetti 1994 [26]</td>
<td>0.31 (0.01–8.29)</td>
<td>0/15</td>
<td>12.7</td>
<td>91</td>
<td>8 (53)</td>
<td>15 (100)</td>
<td>0.39</td>
</tr>
<tr>
<td>Bozzette 1995 [23]</td>
<td>1.08 (0.68–1.72)</td>
<td>42/276</td>
<td>672.0</td>
<td>152</td>
<td>NA</td>
<td>276 (100)</td>
<td>0.62</td>
</tr>
</tbody>
</table>

(continued)
tions, the event rates for Pneumocystis carinii pneumonia and single odds ratio of each trial.

Table 2 shows the different estimates for the direct and indirect comparison of two drug regimens for the prophylaxis of Pneumocystis carinii pneumonia. While trimethoprim–sulphamethoxazole showed a clear benefit when compared with the standard treatment aerosolized pentamidine, dapsone/pyrimethamine showed only a relatively weak trend. The odds ratio of trimethoprim–sulphamethoxazole versus aerosolized pentamidine for Pneumocystis carinii pneumonia was 0.48 (95% confidence interval 0.36 to 0.65) and for dapsone/pyrimethamine versus aerosolized pentamidine 0.89 (95% confidence interval 0.68 to 1.17). For both sets of paired comparisons the test for homogeneity was not statistically significant.

For the indirect comparisons of trimethoprim– sulphamethoxazole versus dapsone/pyrimethamine the odds ratio was considerably lower than the point estimate derived from trials that allowed for the direct comparisons of trimethoprim–sulphamethoxazole and dapsone/pyrimethamine. The odds ratio from indirect comparison was 0.37 (95% confidence interval 0.21 to 0.65) favoring trimethoprim–sulphamethoxazole over dapsone/pyrimethamine for the prevention of Pneumocystis carinii pneumonia. The odds ratio for Pneumocystis carinii pneumonia from the eight trials that compared the drugs directly was 0.64 (95% confidence interval 0.45 to 0.90, test for heterogeneity p = 0.41).

This direct meta-analysis provides support for the superiority of trimethoprim–sulphamethoxazole over dapsone/pyrimethamine for the prevention of Pneumocystis carinii pneumonia, which is consistent with the results from the direct comparisons presented in Table 2.
TABLE 3. Differences in baseline characteristics of randomized controlled trials selected for the indirect comparison of either trimethoprim-sulfamethoxazole or dapsone/pyrimethamine with aerosolized pentamidine for prophylaxis of *Pneumocystis carinii* pneumonia in patients with HIV infection

<table>
<thead>
<tr>
<th>Type of comparison</th>
<th>No. of trials in comparison</th>
<th>Mean person years follow-up</th>
<th>Mean CD4 cells (mm$^3$)</th>
<th>AIDS (%)</th>
<th>Antiretroviral therapy (%)</th>
<th>Individual study quality score $^c$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trimethoprim-sulfamethoxazole vs. aerosolized pentamidine</td>
<td>9</td>
<td>1045.9 (256.6)</td>
<td>111.7 (19.1)</td>
<td>59.9 (16.0)</td>
<td>82.7 (5.0)</td>
<td>0.55 (0.04)</td>
</tr>
<tr>
<td>Dapsone/pyrimethamine vs. aerosolized pentamidine</td>
<td>5</td>
<td>2013.0 (596.9)</td>
<td>117.3 (19.1)</td>
<td>45.8 (11.3)</td>
<td>74.8 (10.5)</td>
<td>0.61 (0.09)</td>
</tr>
</tbody>
</table>

Abbreviations: AIDS = acquired immune deficiency syndrome; HIV = human immunodeficiency virus; SE = standard error.

$^c$SE in parentheses.

To explore the possible reasons for the differences in the magnitude of the effect in the indirect and direct comparisons, we first examined whether there were differences in important prognostic cofactors in trials comparing either trimethoprim-sulfamethoxazole or dapsone/pyrimethamine with pentamidine. We looked at the following variables: CD4 cell count, time of follow-up, the number of patients with antiretroviral therapy at the start of the trial, and the methodologic quality of the study [27] and found no statistically significant differences (Table 3). We then explored whether such differences existed in trials that were included in either direct or indirect comparison (Table 4).

There was a trend showing that patients in trials with direct comparisons were somewhat less immunosuppressed with a higher mean CD4 cells at study entry (group mean 126.2 versus 113.7, $p = 0.48$) and were less likely to have a diagnosis of AIDS (41.9% versus 54.7%, $p = 0.43$). Trials with direct comparisons had a longer follow-up than the ones with indirect comparison (mean person follow-up 1990.7 versus 1391.3, $p = 0.59$). The numbers of patients with antiretroviral therapy at study onset were similar in trials with direct or indirect comparisons. Trials included with direct comparisons had comparable methodologic quality scores as trials included with indirect comparisons.

DISCUSSION

We have presented an alternative to simple comparisons of treatment arms for dealing with situations when randomized

### TABLE 4. Differences in baseline characteristics of randomized controlled trials included in either direct or indirect meta-analytic comparison on the efficacy of two drug regimens compared to standard prophylaxis of *Pneumocystis carinii* pneumonia in patients with HIV infection

<table>
<thead>
<tr>
<th>Type of comparison</th>
<th>No. of trials in comparison</th>
<th>Mean person years follow-up</th>
<th>Mean CD4 cells (mm$^3$)</th>
<th>AIDS (%)</th>
<th>Antiretroviral therapy (%)</th>
<th>Individual study quality score $^c$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direct comparison</td>
<td>Trials comparing trimethoprim-sulfamethoxazole with dapsone/pyrimethamine</td>
<td>8</td>
<td>1990.7 (928.7)</td>
<td>126.2 (9.3)</td>
<td>41.9 (8.1)</td>
<td>83.6 (6.4)</td>
</tr>
<tr>
<td>Indirect comparison</td>
<td>Trials comparing trimethoprim-sulfamethoxazole or dapsone/pyrimethamine with aerosolized pentamidine</td>
<td>14</td>
<td>1391.3 (285.9)</td>
<td>113.7 (12.0)</td>
<td>54.7 (10.8)</td>
<td>80.3 (4.6)</td>
</tr>
</tbody>
</table>

Abbreviations: AIDS = acquired immune deficiency syndrome; HIV = human immunodeficiency virus; SE = standard error.

$^c$SE in parentheses.

$^c$Quality scores according to Chalmers et al. [27]: minimum value 0, maximum value 1.
trials comparing two innovative treatments with placebo or standard treatment, but not comparing the two treatments directly with one another, are available. Our model is also based on meta-analysis, but instead of direct comparison of treatment arms, it compares the magnitude of treatment effects in randomized trials of the interventions in comparison to placebo or control groups.

Our example demonstrates that while this new model protects against some biases, it may still lead to an inaccurate estimate of treatment effect. We had access not only to indirect, but to direct comparison of treatment effects, and found that the indirect comparison led to a substantial overestimation of the relative effectiveness of trimethoprim-sulphamethoxazole relative to dapsone/pyrimethamine when compared with the estimate derived from trials with direct comparisons. Considering why this might be involves reviewing the reasons a meta-analysis utilizing indirect comparisons might yield an inaccurate estimate of relative effectiveness.

One reason for discrepancies in effect sizes between direct and indirect comparison could be related to the different efficiency of the two methods to assess underlying treatment effects. We have tried to assess the efficiency of the two methods.

From equation 5 (see appendix), we see that Var [ln OR_{ind}] is made up of two components, the variances associated with the AB and CB studies. To consider the efficiency of the indirect method, suppose for simplicity that all the studies have the same weight w. Then the variance of the indirect estimate is equal to (g + h)/w.

In contrast, consider the estimation of OR_{AC} if it were possible to carry out direct comparison studies, with the same number of patients as in the indirect studies. Then there would be twice as many patients per group available (assuming equal group sample sizes), and hence the variance would be (g + h)/2w. In other words, if one had the choice of allocating subjects into direct or indirect comparison studies, the direct method would be twice as efficient as the indirect method. Note, however, that in practice meta-analyses are carried out on existing studies, so the precision of the estimated AC effect is not under the control of the analyst; questions of efficiency are therefore somewhat moot.

Studies of one treatment may be methodologically inferior with, for example, randomization open to manipulation, or inadequate blinding. Typically, these deficiencies will lead to overestimates of treatment effect [28]. While we were unable to detect methodologic differences, this does not exclude their presence.

A second source of bias may be in the measurement of outcomes. Criteria for, or the thoroughness with which the diagnosis of Pneumocystis carinii pneumonia is sought may differ in trials of one drug against standard care versus the other against standard care. The length of follow-up may also differ. For example we found that trials used for direct comparison followed study subjects for an appreciably longer time. The likelihood that patients included in these trials experience an event as a consequence of the continuing deterioration of their immune system, or switch to less powerful drugs because of side effects, is considerably higher than in trials with a shorter follow-up. This difference in length of follow-up may therefore explain the smaller difference in treatment effect we observed in the direct comparisons.

Finally, the efficacy of treatment may differ in subpopulations of patients. Treatment may have a larger impact in less severely affected patients, in older or younger patients, or in more compliant groups. We found that patients in the direct comparison trials had less advanced HIV infection with higher CD4 cell counts and fewer patients with AIDS. These important differences in baseline characteristics and study design may illustrate to some extent why the indirect comparison lead to a bigger effect size than the one derived from direct comparison. Considering these issues, one could easily imagine a treatment of equal effectiveness showing greater impact if tested in more responsive populations.

Is it possible that direct and indirect comparisons yield different results but that both are valid? This would occur if the difference between treatments A and C differed in different populations (say, populations X and Y). Assume the direct comparisons of A versus C all included only population X, and the indirect comparisons (involving trials of A versus B and C versus B) only included population Y. Were this the case, then the direct comparisons would yield valid estimates of the effect of A versus C in population X, and the indirect comparisons would yield valid estimates A versus C in population Y. In the current example, we found no such clear differences in the populations included in the direct and indirect comparisons.

Is the primacy of the direct comparisons threatened if the direct comparison trials are methodologically weaker than the indirect comparison trials? In this situation, the indirect comparisons may indeed yield a more accurate estimate of treatment effect. Unfortunately, if direct and indirect estimates differ under these circumstances, either or both of methodological superiority of the indirect comparison trial or underlying differences in the populations could explain the differences. There would be no way of distinguishing between these possibilities. In the current example, the similarity of the methodological quality of the direct and indirect comparison trials reduces this particular concern.

In the example we presented, we can only speculate on whether the differences between the trials explain the different estimates of treatment effect. Thus, our findings suggest that the strength of inference associated with indirect comparisons is inevitably limited, even in the absence of demonstrable sources of bias. Given the inevitable limitations of indirect comparisons, clinicians may put greater weight on factors other than apparent relative effectiveness in choosing between treatments. These factors may include toxicity, convenience, and cost.

This is not to say that indirect comparisons should be
discarded altogether. Better quality trials, more precise estimates of effectiveness, greater similarity between the populations, and larger differences in effectiveness estimates between treatments all add weight to a finding from indirect comparison of differences between two treatments’ effect.

In conclusion, summary estimates in meta-analysis should be based on direct comparisons whenever possible. Indirect comparisons, when undertaken, should involve comparisons of the magnitude of effect in the two sets of controlled trials, rather than focusing exclusively on the treatment arms. Investigators making indirect comparisons should look carefully for differences in methodology, outcome measurement, or the populations included in studies of the two drugs. Even in the absence of evident differences, the strength of inference from indirect comparisons is limited, and if the questions is important then direct comparisons should be undertaken. In the absence of such comparisons, considerations other than relative drug effectiveness gain greater importance in making treatment decisions.

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**APPENDIX**

**Effect Size Estimate**

Suppose that the outcome rate for patients on treatment A in subgroup i is \( P_{Ai} \) and similarly for the other treatments. Subgroups might be defined in terms of age, severity of disease, or other relevant covariates. For comparisons treating A and B in subgroup i the treatment effect might be assessed through the odds ratio

\[
OR_{AB}(i) = \frac{P_{Ai}}{1 - P_{Ai}} \frac{1 - P_{Bi}}{P_{Bi}}
\]

An overall estimate of treatment effect can be obtained from the Mantel-Haenszel method, for instance, as a weighted average of the subgroup estimates, e.g.,

\[
OR_{AB} = \sum w_i \cdot OR_{AB}(i)/\sum w_i
\]

where \( w_i \) is a suitable weight reflecting the variance of the estimate \( OR_{AB}(i) \) [29]. A similar comparison from the C versus B studies gives

\[
OR_{CB} = \frac{\sum w_i \cdot OR_{CB}(i)/\sum w_i}{w_i}
\]

where \( w_i \) denotes a weight appropriate to the CB studies, in general not equal to \( w_i \).

The ratio of (1) and (2) provides the indirect estimate of the difference in effect between treatments A and C. Note that if \( OR_{AB}(i) = OR_{AB} \) and (II) \( OR_{CB}(i) = OR_{CB} \), then the ratio becomes

\[
\frac{OR_{AB}}{OR_{CB}} = \frac{OR_{AB}}{OR_{CB}}
\]

where \( OR_{AB} \) is, conceptually, the A versus C odds ratio for any subgroup that is in common between the AB and CB studies. The special conditions (I) and (II) are equivalent to no treatment × subgroup interaction in either set of studies. Result (3) indicates that if no such interaction is present, the indirect estimate is consistent for the true AC odds ratio. A log transformation of (3) yields

\[
\ln(OR_{AB}) = \ln(OR_{AB}) - \ln(OR_{CB})
\]

Because \( OR_{AB} \) and \( OR_{CB} \) are estimated from different studies, they are statistically independent, and hence the variance of \( OR_{AB} \) can be obtained from

\[
\text{Var}(\ln OR_{AB}) = \text{Var}(\ln OR_{AB}) + \text{Var}(\ln OR_{CB})
\]

**Derivation of the Test Statistics**

In meta-analysis the overall measure of association, \( \gamma \) (such as the odds ratio) is usually taken as a weighted average of the measure from the k individual studies, with weights being the inverse of the variance for each study, as in equation (1). Following Feiss [29], under a null hypothesis of no association in any of the k studies (\( \gamma = 0 \)), then \( \chi^2_{\text{observed}} = \sum w_i \gamma^2 \) is distributed approximately as \( \chi^2 \) with k degrees of freedom, i.e., \( \chi^2 \). The statistic

\[
\chi^2_{\text{observed}} = (\Sigma w_i)^2(\Sigma w)
\]

is distributed as \( \chi^2 \), and measures the average association across the studies. To assess the variation between studies, the term

\[
\chi^2_{\text{homoogeneity}} = \chi^2_{\text{observed}} - \chi^2_{\text{homoogeneity}}
\]

is used, distributed as \( \chi^2_{k-1} \). Note also that

\[
\chi^2_{\text{homoogeneity}} = \Sigma w_i(\gamma - \gamma)^2
\]

Let us now consider the situation where g studies have compared treatment A to standard treatment B or placebo and h studies have compared treatment C to standard treatment B or placebo. Our interest is in obtaining an indirect estimate of the association of A versus C. For the comparison of A versus B the overall association is given by

\[
\chi^2_{\text{mixed}} = (\Sigma w_i)^2(\Sigma w)
\]

(with the sum being over the AB studies) and its components are

\[
\chi^2_{\text{mixed}} = (\Sigma w_i)^2(\Sigma w)
\]
Indirect Comparison in Meta-Analysis

and

\[ \chi^2_{\text{heterogeneity}} = \sum_{AB} w(y - \bar{y}_{AB})^2. \]

Similarly for the comparison for C versus B, the overall association is given by

\[ \chi^2_{\text{heterogeneity}} = \sum_{CB} w(y - \bar{y}_{CB})^2 \]

and its components are

\[ \chi^2_{\text{heterogeneity}} = (\sum_{CB} w y^2)/\sum_{CB} w \]

and

\[ \chi^2_{\text{heterogeneity}} = \sum_{CB} w(y - \bar{y}_{CB})^2. \]

To obtain an indirect test of the A versus C effect from the paired comparisons of A versus B and of C versus B, first note that the overall measure of variation can be taken as the sum of the total \( \chi^2 \) values from the paired comparisons:

\[ \chi^2_{\text{total}} = \chi^2_{\text{AB paired}} + \chi^2_{\text{CB paired}} \]

which is distributed as \( \chi^2_{1} \).

From (6), note that the association over all studies is measured by

\[ \chi^2_{\text{total}} = (\sum_{AB+CB} w y^2)/\sum_{AB+CB} w \]

which is distributed as \( \chi^2_{1} \). The heterogeneity among all studies is, from (7), measured by

\[ \chi^2_{\text{heterogeneity}} = \sum_{AB+CB} w(y - \bar{y})^2 \]

which is distributed as \( \chi^2_{1} \).

For the indirect comparison of treatment A versus treatment C, we propose the statistic \( \chi^2_{\text{AC indirect}} \), being the difference of the overall heterogeneity (equation 7) and the component AB and BC measures of heterogeneity, i.e.,

\[ \chi^2_{\text{AC indirect}} = \chi^2_{\text{heterogeneity}} - \chi^2_{\text{AB heterogeneity}} - \chi^2_{\text{BC heterogeneity}} \tag{9} \]

We now show that \( \chi^2 \) is distributed approximately as \( \chi^2_{1} \), and can be used to test \( H_0: \bar{y}_{AB} = \bar{y}_{BC} \), i.e., to provide the indirect test of treatment A versus treatment C. From the definitions of the terms of the right-hand side of (9), we have

\[ \chi^2_{\text{AC indirect}} = \sum_{AB} w(y - \bar{y})^2 - \sum_{AB} w(y - \bar{y})^2 \]

Expanding each of the squares, terms in \( y^2 \) cancel, leaving

\[ \chi^2_{\text{AC indirect}} = \sum_{AB} w(y - \bar{y})^2 + 2 \sum_{AB} w \bar{y}_{AB} y \]

\[ + 2 \sum_{CB} w \bar{y}_{CB} \bar{y} + \sum_{AB+CB} w y^2 - \sum_{AB} w \bar{y}_{AB}^{2} \]

\[ - \sum_{CB} w \bar{y}_{CB}^{2} = \sum_{AB} w \bar{y}_{AB}^{2} + \sum_{CB} w \bar{y}_{CB}^{2} \]

\[ - \sum_{AB+CB} w y^2 \]

Now \( \bar{y} \) is a weighted average of the mean effect sizes in the AB and CB studies, so

\[ \bar{y} = \frac{\bar{y}_{AB} \sum_{AB} w + \bar{y}_{CB} \sum_{CB} w}{\sum_{AB} w + \sum_{CB} w} \]

Substituting from (11) and (10) and then simplifying, we have that

\[ \chi^2_{\text{AC indirect}} = \frac{(\bar{y}_{AB} - \bar{y}_{CB})^2 (\sum_{AB} w)(\sum_{CB} w)}{\sum_{AB} w + \sum_{CB} w} \]

Thus testing \( H_0: y_{AB} = y_{BC} \) and hence the indirect AC comparison of interest.