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RESEARCH-IN-BRIEF

A little-known perspective on the I-squared statistic

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Abstract

The I-squared statistic has become hugely popular in meta-analysis. Motivated by the recent statement that 'Informally, it can be considered to reflect the extent to which confidence intervals displayed in a forest plot do not overlap with each other', this short note formalises this perspective. The insights provided by our analysis lend further weight to the interpretation of the I-squared statistic as a measure of inconsistency. This perspective reminds us that visual inspections of forest plots are vitally important when assessing between-study variation.

Highlights

What is already known?

The I-squared statistic has enjoyed considerable success in meta-analysis. It has recently been stated that, informally, I-squared can be considered to reflect the extent to which confidence intervals displayed in a forest plot do not overlap with each other.

What is new?

We investigate mathematically how I-squared is calibrated to the extent to which confidence intervals do, and do not, overlap. By doing so, we are able to formalise this interpretation of I-squared.

Potential impact for RSM readers

Readers may not be aware of this particular interpretation of I-squared. Our work opens up possibilities, based on forest plots and confidence interval overlap, for measuring inconsistencies in trial results in meta-analysis.

1. Introduction

The I-squared statistic,[1,2] hereafter referred to as I^2, has enjoyed considerable success in meta-analysis, to the extent that it will require no introduction to those already familiar with the standard meta-analytic toolkit. Higgins and López-López[3] recently reflected on this statistic and it is a comment made in their paper that motivated the work presented here.

We recognise the limitations of I^2 statistics, which mostly arise from misunderstanding what they measure.[4–6] However, as explained by Higgins and López-López,[3] I^2 helps to overcome some of the

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limitations of other measures, such as tests for heterogeneity and the estimated between-study variance. Furthermore, I^2 is important in determining the performance of standard methods for meta-analysis,[7] and so is useful in theoretical work. This note also sits in the realm of theoretical work and draws on relatively simple statistical results, such as basic properties of the multivariate normal distribution, means and variances, and elementary combinatorics.

This work was motivated by two sentences from Higgins and López-López,[3] who state that 'Informally, [I^2] can be considered to reflect the extent to which confidence intervals displayed in a forest plot do not overlap with each other. This is the rationale for the characterization of I^2 as a measure of *inconsistency*', where the italics are theirs, not ours. This perspective is one that is rarely contemplated or discussed, even by experienced meta-analysts. In this note, we will formalise this statement mathematically and explore its potential implications. This will help us to understand some interesting properties of the I^2 statistic that may not be widely appreciated.

2. Another perspective

We take equation (3) from Higgins and López-López[3] as our conceptual starting point, namely,

$$I^2 = \frac{\tau^2}{\sigma^2 + \tau^2}, \tag{1}$$

where τ^2 is the between-study variance parameter and σ^2 is a measure of within-study variance. This presentation is cosmetically different from equation (3) in Higgins and López-López[3] because they use i^2 to represent this 'parametric form' of the computed statistic and they also present this as a percentage. As explained by Higgins and López-López,[3] σ^2 is a clearly defined parameter only if all studies have the same within-study variance. Otherwise, σ^2 needs to be interpreted as a 'typical' within-study variance across the studies included in the meta-analysis. There are numerous different ways for computing a 'typical' within-study variance[3] and equation (9) from Higgins and Thompson[1] is conventionally used for this purpose. For the purposes of theoretical work,[7] it simplifies matters to assume that the study sizes are not too disparate so that this typical within-study variance is representative of all studies. To simplify presentation, we will 'assume' that all studies have the same within-study variance σ^2, but, in reality, this is just an approximation whose accuracy will depend on the distribution of the within-study variances. Our main focus lies in how the probability that study-specific confidence intervals do, and do not, overlap depends on I^2, motivated by the statement made by Higgins and López-López.[3]

2.1. The probability that confidence intervals in a forest plot overlap

Consider, without loss of generality, the first two study estimates under the random-effects model,[8,9] $Y_1 \sim N(\mu, \sigma^2 + \tau^2)$ and $Y_2 \sim N(\mu, \sigma^2 + \tau^2)$. Assuming that the within-study variances are known without error, the corresponding 95% confidence intervals, displayed on a forest plot, are given by $(Y_1 - 1.96\sigma, Y_1 + 1.96\sigma)$ and $(Y_2 - 1.96\sigma, Y_2 + 1.96\sigma)$. If $-2 \times 1.96\sigma < Y_2 - Y_1 < 2 \times 1.96\sigma$, then their 95% confidence intervals overlap. This is because these confidence intervals extend 1.96σ in each direction from Y_1 and Y_2, so that we have overlap if the absolute difference between the point estimates is less than $2 \times 1.96\sigma$. Let us define $D = Y_2 - Y_1 \sim N(0, 2(\sigma^2 + \tau^2))$. Then the probability that the 95% confidence intervals in a forest plot overlap, $P(\text{overlap})$, is

$$P(\text{overlap}) = P(-2 \times 1.96\sigma < D < 2 \times 1.96\sigma).$$

Defining $Z = D/\sqrt{2(\sigma^2 + \tau^2)} \sim N(0, 1)$, we can write this as

$$P(\text{overlap}) = P\left(-\sqrt{2} \times 1.96\sqrt{\frac{\sigma^2}{\sigma^2 + \tau^2}} < Z < \sqrt{2} \times 1.96\sqrt{\frac{\sigma^2}{\sigma^2 + \tau^2}}\right).$$

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Then, from the definition of I^2 in equation (1),

$$P(\text{overlap}) = P\left(-\sqrt{2} \times 1.96\sqrt{1 - I^2} < Z < \sqrt{2} \times 1.96\sqrt{1 - I^2}\right).$$

Noting that Z is standard normal, this is

$$P(\text{overlap}) = \Phi(\sqrt{2} \times 1.96\sqrt{1 - I^2}) - \Phi(-\sqrt{2} \times 1.96\sqrt{1 - I^2}),$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. The key function is $f(I^2) = \sqrt{2} \times 1.96\sqrt{1 - I^2}$. Using this definition, we have

$$P(\text{overlap}) = \Phi(f(I^2)) - \Phi(-f(I^2)).$$

There are many equivalent ways to write this quantity but we cannot make further analytical progress. From the symmetry of the normal distribution, $\Phi(-x) = 1 - \Phi(x)$, we can write this as

$$P(\text{overlap}) = 2\Phi(f(I^2)) - 1. \tag{2}$$

There are $n(n-1)/2$ pairs of confidence intervals, where n is the number of studies. Therefore, the expected number of pairs of confidence intervals that overlap on a forest plot, $E(\text{overlap})$ is

$$E(\text{overlap}) = \frac{n(n-1)}{2} P(\text{overlap}). \tag{3}$$

If $I^2 = 1/2$, then $f(I^2) = 1.96$, so that $P(\text{overlap}) = 2\Phi(1.96) - 1 = 0.95$. Hence, if $I^2 = 1/2$, then the probability of confidence interval overlap is equal to the coverage probability of the confidence intervals. The function $f(I^2)$ is decreasing in I^2, and $P(\text{overlap})$ in equation (2) is increasing in $f(I^2)$, so that $P(\text{overlap})$ is decreasing in I^2. This investigation therefore formalises the statement made by Higgins and López-López[3] that I^2 can be considered to reflect the extent to which confidence intervals displayed in a forest plot do not overlap with each other. Equation (2) describes this intuition in simple and direct mathematical form.

2.2. The probability that confidence intervals in a forest plot do not overlap

Higgins and López-López[3] focus on I^2 as reflecting the extent to which confidence intervals displayed in a forest plot *do not* overlap with each other. We have instead derived results for the probability that these confidence intervals *do* overlap. We have done this because this simplifies the presentation of our mathematical derivations; we can then evaluate the probability that a normally distributed random variable lies within one interval of finite length ($-2 \times 1.96\sigma < D < 2 \times 1.96\sigma$), instead of two intervals of infinite length ($D > 2 \times 1.96\sigma$ or $D < -2 \times 1.96\sigma$). This becomes more useful in Section 2.5 where we calculate the probability that a bivariate normal random variable lies within a finite square, centred at the origin. However, all our results are easily communicated in terms of $P(\text{not overlap})$, which is simply the complement of equation (2). Furthermore, in Section 2.5, we can easily derive the mean and variance of $1 - O$, which is the proportion of confidence intervals that do not overlap.

2.3. Other straightforward extensions

Critical values other than $k = 1.96$ could also be considered, where natural choices are $k = 1$ and $k = 0.675$. The former value uses error bars of one standard deviation and the latter corresponds to confidence interval coverage of 1/2, so that these two values capture typical variation in two different senses. Alternatively, critical values corresponding to other significance levels could also be used. If an alternative value to $k = 1.96$ is used, then the key function becomes $f(I^2, k) = \sqrt{2} \times k\sqrt{1 - I^2}$

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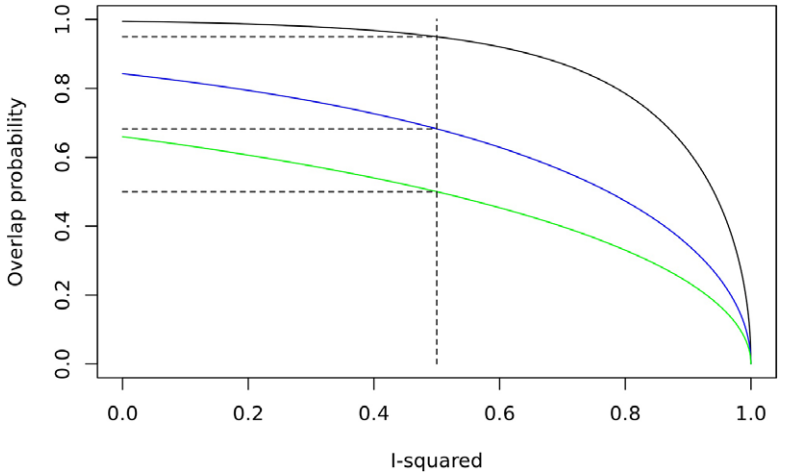


Figure 1. *Probability of confidence interval overlap as a function of* I^2 *for* $k = 0.675$ *(green),* $k = 1$ *(blue), and* $k = 1.96$ *(black). Dotted lines at* $I^2 = 1/2$ *and the corresponding confidence interval overlap probabilities are also shown to aid interpretation.*

and all formulae then apply with this new function. If $k = 1.96$, then all results simplify to those given previously, so that $f(I^2, 1.96) = f(I^2)$. However, using alternatives to $k = 1.96$ would require access to the meta-analytic dataset. This is because forest plots are rarely, if ever, presented using alternatives to 95% confidence intervals. This information may however be deducible in some instances from reported aggregate-level information. In practice, without this, it may in any case often be difficult to determine if confidence intervals in published forest plots overlap. This may need to be determined using high-level scans of these plots, and a keen eye or specialist software, unless these confidence intervals are also displayed numerically.

The above analysis required to compute $P(\text{overlap})$ in equation (2) is straightforward to generalise to the case where every study has different σ_i^2. If desired, $E(\text{overlap})$ in equation (3) could then be computed by summing the $n(n-1)/2$ different values of study pair specific $P(\text{overlap})$. However, the connection with I^2 would then be lost. The motivation for I^2 in any case rests on the assumption that a typical within-study variance is suitable. Hence, when investigating the implications of I^2 statistics mathematically, it is therefore probably most appropriate to consider the case where all studies have the same within-study variance, as we have here.

2.4. Numerical results

In Figure 1, we show the overlap probability (equation (2)) as a function of I^2 for three values of $k = 0.675$ (green), 1 (blue), and 1.96 (black). We also show a vertical dotted line at $I^2 = 1/2$ and horizontal lines connecting the curves to the vertical axis at the overlap probabilities, at $I^2 = 1/2$, of 1/2, $2\Phi(1) - 1 = 0.683$ and 0.95, to aid interpretation. The probability that confidence intervals overlap is not very sensitive to the value of I^2 until this becomes larger than 1/2, but nevertheless the connections between I^2 and $P(\text{overlap})$ are clear.

In Figure 2 (left), we show the essential elements of a conventional forest plot for an example[10] that has been used many times previously in methods work. Briefly, this example includes 26 studies exploring the effectiveness of writing-to-learn interventions. With 26 studies, there are $26 \times 25/2 = 325$ pairs of confidence intervals that may, or may not, overlap. A standard random-effects meta-analysis, using the DerSimonian and Laird estimator[9] of τ^2, using the metafor package[11] provided $I^2 = 55.9\%$. Metafor was also used to compute a 95% confidence interval for I^2 of (31.8%, 82.2%).

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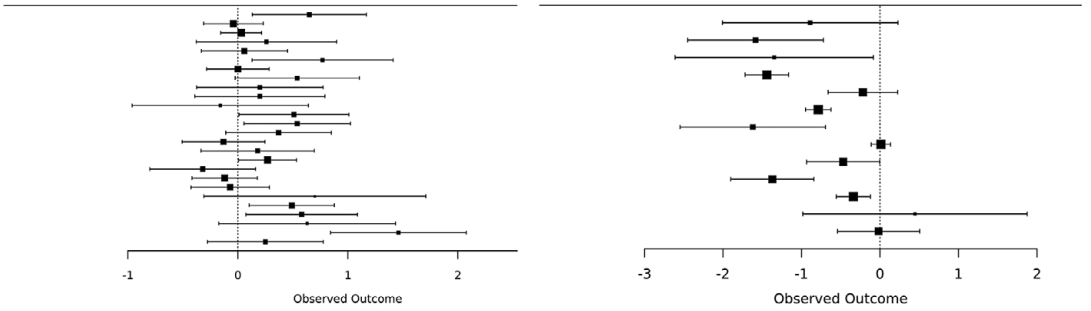


Figure 2. *Essential elements of forest plots examples exploring the effectiveness of writing-to-learn interventions (left) and the BCG vaccine against tuberculosis (right).*

A computer program was written to enumerate the number, and proportion, of overlapping 95% confidence intervals in Figure 2 (left). This computed that $311/325 = 95.7\%$ of the pairs of confidence intervals in Figure 2 (left) overlap. The majority of 95% confidence intervals therefore overlap, which might be thought to be contradictory to the quite large $I^2 = 55.9\%$. However, computing the overlap probability (equation (2)) with $I^2 = 55.9\%$ gives 93.4%. Repeating this calculation with $I^2 = 31.8\%$ and 82.2% gives 97.8% and 75.8%. Hence, the I^2 statistic for this example can be seen to be in good agreement with the proportion of overlapping confidence intervals (Figure 2, left).

In Figure 2 (right), we show the essential elements of a conventional forest plot for another familiar example. Briefly, this example includes 13 studies exploring the effectiveness of the BCG vaccine against tuberculosis and was taken from the metafor package.[11] This example displays very considerable between-study variation. Analysis, conducted in the same way for the previous example, resulted in $I^2 = 92.1\%$, with 95% confidence interval (81.9%, 97.7%). Here, 55 of the 78 (70.5%) pairs of confidence intervals overlap. Computing the overlap probability (equation (2)) with $I^2 = 92.1\%$ gives 56.4%. Repeating this calculation with $I^2 = 81.9\%$ and 97.7% gives 76.2% and 32.6%. Hence, the I^2 statistic for this example can also be seen to be in agreement with the proportion of overlapping confidence intervals (Figure 2, right).

We have used two examples with notable between-study heterogeneity because, as noted above, the probability of confidence interval overlap is not sensitive to small values of I^2 (Figure 1). For examples with moderate or mild I^2, for example, less than 30%, the vast majority of 95% confidence intervals will overlap. For examples such as these, analyses like the ones we have conducted would be much less interesting. This is because the conclusion that nearly all confidence intervals overlap, in agreement with the mild I^2 statistic, would be almost inevitable. In practice, our new results will be insightful for more heterogeneous datasets, such as the two we have explored here. The supplementary materials provide data, and R code, to produce all numerical results.

2.5. Further mathematical considerations

Although the above mathematical analysis requires only very elementary mathematical statistics, we would like to point out some subtle points for those who might consider extending this further. More generally, we might be interested in the properties of the random variable O, defined to be the proportion of confidence intervals in the forest plot that overlap. Let $N = n(n-1)/2$ be the number of pairs of confidence intervals in the forest plot, which may or may not overlap. Place the pairs of confidence intervals in a list and let I_i, $i = 1, 2, \ldots N$, be an indicator that the ith pair in this list overlap. We can then define

$$O = \sum_{i=1}^{N} I_i / N.$$

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Continuing to assume that all studies have the same within-study variance, σ^2, the expected value of O is simply

$$E[O] = \frac{1}{N}\sum_{i=1}^{N} E(I_i) = E(I_i) = P(\text{overlap}),$$

as given previously in equation (2), where $P(\text{overlap})$ is a function of I^2.

However, other properties, such as the variance of O, are harder to derive. This is because some, but not all, I_i are independent. For example, if I_1 relates to the confidence intervals from studies 1 and 2, and I_2 relates to studies 1 and 3, then I_1 and I_2 are dependent. This is because the results from study 1 then contribute to both I_1 and I_2, invoking dependence between them. However, I_1 is independent of I_3, if I_3 relates to studies 3 and 4. This is because estimates from studies 1 and 2 are independent of those from studies 3 and 4. In the former case, I_1 and I_2 'share studies' but in the latter case I_1 and I_3 do not 'share studies' in this way. However, we have that

$$\text{Var}[O] = \text{Var}\left(\frac{1}{N}\sum_{i=1}^{N} I_i\right) = \frac{1}{N^2}\left(\sum_{i=1}^{N}\text{Var}(I_i) + \sum_{i=1}^{N}\sum_{j=1, j\neq i}^{N}\text{Cov}(I_i, I_j)\right).$$

Hence, because all I_i are Bernoulli with probability $P(\text{overlap})$, we have

$$\text{Var}[O] = \frac{P(\text{overlap})(1 - P(\text{overlap}))}{N} + \sum_{i=1}^{N}\sum_{j=1, j\neq i}^{N}\text{Cov}(I_i, I_j)/N^2. \tag{4}$$

The main challenge is computing the second term, which consists of covariances, some of which are zero (where I_i and I_j do not 'share studies') and others are non-zero (where I_i and I_j do 'share studies'). Some relatively simple combinatorics come to our rescue. Every I_i shares a study with exactly $2(n-2)$ other I_j. This is because two studies are required to define I_i. This leaves $n-2$ other studies that may be used to define I_j, any of which may be shared with either of the two studies that define I_i. There are $N = n(n-1)/2$ different I_i, so that in total there are $(2(n-2)) \times (n(n-1)/2) = n(n-1)(n-2)$ combinations of I_i and I_j that share studies and so are not independent. Hence, equation (4) is

$$\text{Var}[O] = \frac{P(\text{overlap})(1 - P(\text{overlap}))}{N} + n(n-1)(n-2)\text{Cov}(I_i^*, I_j^*)/N^2, \tag{5}$$

where I_i^*, I_j^* share a study in their definition in equation (5); the superscripts $*$ are intended to emphasise that I_i, I_j 'share studies'. The identity $N = n(n-1)/2$ may be substituted into equation (5) so that, in terms of the dependence of the number of studies, this can be written entirely in terms of n.

The more challenging part is evaluating $\text{Cov}(I_i^*, I_j^*)$ in equation (5). However, this can be computed as $\text{Cov}(I_i^*, I_j^*) = E(I_i^* I_j^*) - E(I_i^*)E(I_j^*)$, where $E(I_i^*) = E(I_j^*) = P(\text{overlap})$. Hence, only $E(I_i^* I_j^*)$ remains to be computed. This is then computed by considering, without loss of generality, the first three estimates Y_1, Y_2, and Y_3, where $I_1^* = 1$ if the confidence intervals from studies 1 and 2 overlap, and $I_2^* = 1$ if those from studies 1 and 3 overlap. Then, under the random-effects model where all studies have the same within-study variance σ^2, we have

$$\begin{pmatrix} Y_1 \\ Y_2 \\ Y_3 \end{pmatrix} \sim N(\mu\mathbf{1}, (\sigma^2 + \tau^2)\mathbf{I}),$$

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where $\mathbf{1}$ is the 3×1 column vector where all entries are one, and $\mathbf{I}$ is the 3×3 identity matrix. Now consider the random variables $D_2 = Y_2 - Y_1$ and $D_3 = Y_3 - Y_1$ that have distribution

$$\begin{pmatrix} D_2 \\ D_3 \end{pmatrix} \sim N\left(\mathbf{0}, (\sigma^2 + \tau^2)\begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix}\right),$$

where $\mathbf{0}$ is the 2×1 column vector where both entries are zero. Then $I_1^* = 1$ if $-2 \times 1.96\sigma < D_2 < 2 \times 1.96\sigma$, and $I_2^* = 1$ if $-2 \times 1.96\sigma < D_3 < 2 \times 1.96\sigma$. Now consider standardised versions $Z_2 = D_2/\sqrt{2(\sigma^2 + \tau^2)}$ and $Z_3 = D_3/\sqrt{2(\sigma^2 + \tau^2)}$, where

$$\begin{pmatrix} Z_2 \\ Z_3 \end{pmatrix} \sim N\left(\mathbf{0}, \begin{pmatrix} 1 & 1/2 \\ 1/2 & 1 \end{pmatrix}\right).$$

Next, $I_1^* = 1$ and $I_2^* = 1$ if $-\sqrt{2} \times 1.96\sqrt{1 - I^2} < Z_2 < \sqrt{2} \times 1.96\sqrt{1 - I^2}$ and $-\sqrt{2} \times 1.96\sqrt{1 - I^2} < Z_3 < \sqrt{2} \times 1.96\sqrt{1 - I^2}$, respectively. This probability is easily computed using standard software, for example, one call of the *pmvnorm* function, from the R package *mvtnorm*, can be used. This is because the region where (Z_2, Z_3) results in confidence interval overlap in both instances is simply a finite square centred at the origin. Furthermore, this probability is equal to $E(I_i^* I_j^*)$, which was the last term required to compute $\mathrm{Cov}(I_i^*, I_j^*)$ in equation (5). Taking the marginal distributions from the bivariate normal for (Z_2, Z_3) above gives the same probability for confidence interval overlap as shown previously in equation (2).

We can therefore write the mean of O solely in terms of I^2 and its variance in terms of I^2 and the number of studies. Simulations suggest that the distribution of O can be very skew, especially when I^2 is moderate or very large. This is because $P(\text{overlap})$ is then either close to 1 or 0, respectively. Perhaps not surprisingly, a Beta distribution, with mean and variance matched to that of O, has been found to provide a reasonable approximation for large n. As in Section 2.3, it is mathematically straightforward, but computationally complex, to generalise to the situation where studies have different within-study variances. The connection with I^2 is then again lost, however. It continues to be straightforward to consider alternative values of k where the analysis in this section simply generalises where 1.96 may be replaced by any other k. One important point of this section is to make it clear that, although the mean of O is easy to compute, other aspects of its distribution are much harder to derive. Hence, this section is intended to provide a 'safety note' for those who might consider taking this work further.

3. Discussion

We have shown mathematically how I^2 relates to the probability of confidence intervals overlapping, and hence to the probability of them not overlapping, on forest plots. Our work is sufficient to show how the distribution of the proportion of overlapping confidence intervals is related to I^2. I^2 statistics have also been proposed in more complicated meta-analytic settings[12] but these have different conceptual bases. It may however be possible to derive new interpretations of these and other measures of heterogeneity in meta-analysis. Study-specific prediction intervals[13] have also been proposed and exploring how they might depend on I^2 and other quantities may be of interest.

Our work may motivate other possibilities, such as basing measures of between-study heterogeneity on the proportions of confidence intervals that overlap and the extent to which multiple (more than two) of these intervals overlap. Other measures of the extent to which confidence intervals 'agree' with each may also be feasible. We leave these ideas as possible avenues for further work.

We tentatively propose that providing the number or proportion of confidence intervals that overlap in a forest plot could be a useful further descriptive statistic. For example, this could be calibrated in terms of its accompanying I^2 statistic to assess if this statistic is performing well in terms of its property of defining inconsistency in this way. By proposing a Beta approximation to O, further methods work and applications are also facilitated. However, it would be audacious, or even foolhardy, to base any

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formal statistical inference on O or variations thereof. A safer implication of our work would be to encourage consumers of systematic reviews to visually inspect forest plots even more carefully than they already do. They could also consider reporting statistics such as O, and a new type of I^2 statistic that is based on 'back-transforming' O to I^2 using the results derived here. Visual inspections of forest plots are vitally important when assessing between-study variation and our work serves to further emphasise this important point.

To summarise, we have uncovered some relatively simple results relating to the interpretation of I^2 as a measure of inconsistency, defined in terms of the probability of confidence interval overlap (or, equivalently, of non-overlap). We hope that this work will be illuminating for those already familiar with the I^2 statistic and encourage them to further appreciate its value. Finally, it is perhaps inspiring to note that this work was motivated by the reflection on two sentences from a recently published paper. This may serve to remind us that, sometimes, a few especially well-chosen words can inspire other researchers.

Author contributions. Conceptualisation: D.J., J.P.T.H., and J.A.L.-L.; Data curation: D.J.; Formal analysis: D.J.; Investigation: D.J. and J.A.L.-L.; Methodology: D.J., J.P.T.H., and J.A.L.-L.; Project administration: D.J.; Validation: J.A.L.-L.; Visualisation: D.J.; Writing—original draft: D.J., J.P.T.H., and J.A.L.-L.; Writing—review and editing: D.J., J.P.T.H., and J.A.L.-L.

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References

[1] Higgins JPT, Thompson SG. Quantifying heterogeneity in a meta-analysis. *Stat Med*. 2002;21(11): 1539–1558. https://doi.org/10.1002/sim.1186.

[2] Higgins JPT, Thompson SG, Deeks JJ, Altman DG. Measuring inconsistency in meta-analyses. *BMJ* 2003;327(7414): 557–560. Group Section: Education and debate. https://doi.org/10.1136/bmj.327.7414.557.

[3] Higgins JPT, López-López JA. Reflections on the I-squared index for measuring inconsistency in meta-analysis. *Res Synth Methods*. 2026;17: 389–402. https://doi.org/10.1017/rsm.2025.10062.

[4] Rücker G, Schwarzer G, Carpenter JR, Schumacher M. Undue reliance on I(2) in assessing heterogeneity may mislead. *BMC Med Res Methodol*. 2008;8: 79. https://doi.org/10.1186/1471-2288-8-79.

[5] Borenstein M, Higgins JPT, Hedges LV, Rothstein HR. Basics of meta-analysis: I2 is not an absolute measure of heterogeneity. *Res Synth Methods*. 2017;8(1): 5–18. https://doi.org/10.1002/jrsm.1230.

[6] Hoaglin DC. Misunderstandings about Q and 'Cochran's Q test' in meta-analysis. *Stat Med* 2016; 35(4): 485–495. https://doi.org/10.1002/sim.6632.

[7] Jackson D, Turner R. Power analysis for random-effects meta-analysis. *Res Synth Methods*. 2017;8(3): 290–302. https://doi.org/10.1002/jrsm.1240.

[8] Higgins JPT, Thompson SG, Spiegelhalter DJ. A re-evaluation of random-effects meta-analysis. *J Royal Stat Soc Ser A Stat Soc*. 2009;172(1): 137–159.

[9] DerSimonian R, Laird N. Meta-analysis in clinical trials. *Control Clin Trials*. 1986;7(3): 177–188. https://doi.org/10.1016/0197-2456(86)90046-2.

[10] Viechtbauer W, Cheung MWL. Outlier and influence diagnostics for meta-analysis. *Res Synth Methods*. 2010;1(2): 112–125. https://doi.org/10.1002/jrsm.11.

[11] Viechtbauer W. Conducting meta-analyses in R with the metafor package. *J Stat Softw*. 2010;36: 1–48. https://doi.org/10.18637/jss.v036.i03.

[12] Jackson D, Law M, Barrett JK, et al. Extending DerSimonian and Laird's methodology to perform network meta-analyses with random inconsistency effects. *Stat Med*. 2016;35(6): 819–839. https://doi.org/10.1002/sim.6752.

[13] Aert VRCM, Schmid CH, Svensson D, Jackson D. Study specific prediction intervals for random-effects meta-analysis: a tutorial. *Res Synth Methods*. 2021;12(4): 429–447. https://doi.org/10.1002/jrsm.1490.

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