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DISCUSSION

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Meta-analyzing partial correlation coefficients using Fisher's z transformation

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Abstract

The partial correlation coefficient (PCC) is used to quantify the linear relationship between two variables while taking into account/controlling for other variables. Researchers frequently synthesize PCCs in a meta-analysis, but two of the assumptions of the common equal-effect and random-effects meta-analysis model are by definition violated. First, the sampling variance of the PCC cannot assumed to be known, because the sampling variance is a function of the PCC. Second, the sampling distribution of each primary study's PCC is not normal since PCCs are bounded between −1 and 1. I advocate applying the Fisher's z transformation analogous to applying Fisher's z transformation for Pearson correlation coefficients, because the Fisher's z transformed PCC is independent of the sampling variance and its sampling distribution more closely follows a normal distribution. Reproducing a simulation study by Stanley and Doucouliagos and adding meta-analyses based on Fisher's z transformed PCCs shows that the meta-analysis based on Fisher's z transformed PCCs had lower bias and root mean square error than meta-analyzing PCCs. Hence, meta-analyzing Fisher's z transformed PCCs is a viable alternative to meta-analyzing PCCs, and I recommend to accompany any meta-analysis based on PCCs with one using Fisher's z transformed PCCs to assess the robustness of the results.

KEYWORDS

Fisher's z transformation, meta-analysis, partial correlation coefficient, sampling variance

Highlights

What is already known

- The assumptions of the equal-effect and random-effects meta-analysis model are by definition violated when partial correlation coefficients are meta-analyzed
- Meta-analyses based on partial correlation coefficients are biased

What is new

- Meta-analyzing Fisher's z transformed partial correlation coefficients is a viable alternative when meta-analyzing partial correlation coefficients
- Meta-analysis based on Fisher's z transformed partial correlation coefficient had the lowest bias and root mean square error compared to meta-analyzing partial correlation coefficients in the simulation study design of Stanley and Doucouliagos's study. Moreover, coverage rates of meta-analysis based on Fisher's z transformed partial correlation coefficient were close to the nominal coverage rate.

Potential impact for RSM readers outside the authors' field

- Researchers conducting a meta-analysis based on partial correlation coefficients are recommended to accompany a meta-analysis based on Fisher's z transformed partial correlation coefficient to study the robustness of the results

1 | INTRODUCTION

Partial correlation coefficients (PCC) are commonly used in meta-analyses to synthesize studies on the relationship between two continuous variables while controlling for the effect of other variables. Van Aert and Goos[1] studied the statistical properties of two estimators of the sampling variance of the PCC. The estimating equation of the first estimator is (see Olkin and Siotani[2] and chapter 4 of Anderson[3])

$$s_1^2 = \frac{\left(1-r_p^2\right)^2}{df}. \quad (1)$$

where r_p is the estimated PCC and df refers to the degrees of freedom that are $N-M-1$ with N being the total sample size and M the number of independent variables in a linear regression model. This estimating equation is the large-sample approximation of the sampling variance of the PCC where the true PCC is replaced by r_p. The second estimating equation of the sampling variance of the PCC is[4]

$$s_2^2 = \frac{1-r_p^2}{df}. \quad (2)$$

This estimating equation is derived conditional on the true PCC being equal to zero. Van Aert and Goos[1] showed in an analytical study that s_1^2 is less biased than s_2^2 for different values of the true PCC and different sample sizes.

Stanley and Doucouliagos[5] (henceforth S&D) conducted a simulation study to examine the effect of including s_1^2 and s_2^2 as part of the weights in the random-effects meta-analysis model. The conclusion of their simulation study is in the title of their paper: "Correct SEs can bias meta-analysis," so using s_1^2 yielded more biased results in the meta-analysis than s_2^2. S&D[5] attribute this larger bias to larger differences in the inverse variance weights when s_1^2 is used compared to s_2^2. That is, the primary studies in the meta-analysis get more equal weights when s_2^2 is used compared to s_1^2. These results corroborate previous research[6,7] that using unit weights in a random-effects meta-analysis model had comparable or better statistical properties than inverse variance weights.

Meta-analyzing PCCs as S&D did in their simulation study and as is commonly done in practice[8–13] violates the assumptions of the commonly used equal-effect (a.k.a. fixed-effect or common-effect) and random-effects meta-analysis models.[14] The assumption of known sampling variances is by definition violated for PCCs, because the estimate r_p is in the estimating equation of the sampling variance. An additional consequence of this is that the sampling variance of the PCC is dependent on r_p, and this is ignored in the meta-analysis models. Note that this assumption is also violated for other popular effect size measures (e.g., Pearson correlation coefficients, Cohen's d, Hedges' g, and log odds ratios). Another assumption of the meta-analysis models, that is by definition violated when PCCs are used as effect size measure, is that the sampling distribution of each primary study's effect size follows a normal distribution. PCCs are bounded between -1 and 1, so the violation of this normality assumption becomes more severe the more the true PCC differs from zero.

The goal of this paper is to advocate the use of another approach to meta-analyze PCCs by meta-analyzing the Fisher's z transformed PCCs. This approach

is especially preferred over meta-analyzing PCCs for the conditions with a large true PCC that S&D included in their simulation study. Fisher's z transformation for PCCs is included in the next section of the paper, and it is explained why this approach is more in line with the assumptions of the meta-analysis models. Section 3 reproduces the simulation study of S&D where the meta-analysis based on Fisher's z transformed PCCs has been added. The last section of this paper is a discussion that also contains recommendations for applied researchers.

2 | META-ANALYZING FISHER'S z TRANSFORMED PCCS

The procedure for applying Fisher's z transformation to PCCs is analogous to the Fisher's z transformation for Pearson correlation coefficients, because the probability density function of the PCC is the same as of the Pearson correlation coefficients except for the degrees of freedom.[15] The degrees of freedom are different, because these are corrected for the number of control variables in the linear regression model. A Fisher's z transformed PCC can be computed with (see Fisher[15] and section 4.3 of Anderson[3])

$$\tanh^{-1}(r_p) = 0.5 \times \log\left(\frac{1+r_p}{1-r_p}\right), \tag{3}$$

and its sampling variance is equal to

$$s_3^2 = \frac{1}{N-3-(M-1)}. \tag{4}$$

When Fisher's z transformed PCCs are meta-analyzed, the (average) effect size estimate is commonly transformed to a PCC to facilitate interpretation using

$$\tanh(F_z) = \frac{e^{2\times F_z}-1}{e^{2\times F_z}+1} \tag{5}$$

where F_z is the meta-analytic estimate based on the Fisher's z transformed PCCs.

Meta-analyzing Fisher's z transformed PCCs is more in line with the assumptions of the meta-analysis models compared to meta-analyzing PCCs. The Fisher's z transformation is a variance-stabilizing transformation, so the sampling variance estimated with s_3^2 does not depend on the Fisher's z transformed PCC. Moreover, the Fisher's z transformed PCC also more closely follows a normal distribution than the PCC, and this is especially the case if the true PCC is different from zero. However, it has to be noted that the assumptions of known sampling variance and that the sampling distribution of each primary study's effect size follows a normal distribution are still violated when meta-analyzing Fisher's z transformed PCCs. The estimating equation s_3^2 is a large-sample approximation and the sampling distribution of the Fisher's z transformed PCCs only approximately follows a normal distribution, but these approximations are considered to be accurate even for small sample sizes.[16,17]

3 | REPRODUCING SIMULATION STUDY BY STANLEY AND DOUCOULIAGOS

S&D[5] briefly mentioned the option for meta-analyzing Fisher's z transformed PCCs rather than PCCs: "For the sake of robustness or if in doubt, it [is] always wise to convert partial correlations to Fisher's z" (p. 519). However, they did not include a meta-analysis based on Fisher's z transformed PCCs in their simulation study while the selected conditions with a true PCC being substantially different from zero (i.e., 0.7071 and 0.3162) are not advantageous to meta-analyzing PCCs. The large true PCC causes a large negative correlation between the sampling variance and the PCC and the sampling distribution of each primary study's effect size strongly deviates from a normal distribution for a true PCC of this size. I reproduced the simulation study of S&D and added random-effects meta-analysis based on Fisher's z transformed PCCs to the simulations.[1] The simulation study was reproduced using R[29] (Version 4.2.3). R code of the simulation study is available at https://osf.io/ubqfg.

Table 1 presents the results of reproducing the simulation study of S&D. The results based on s_1^2 and s_2^2 are similar to those reported in S&D except for small differences due to Monte-Carlo error. The results of the meta-analyses based on Fisher's z transformed PCCs are in the columns "Fisher's z." Bold values indicate the approach that was the least biased, had the lowest root mean square error (RMSE), or where its coverage was closest to the nominal coverage rate of 0.95 for a particular condition. Bias and RMSE was always the lowest for meta-analyses based on Fisher's z transformed PCCs. Coverage of meta-analyses based on Fisher's z transformed PCCs was close to 0.95 for all conditions. As expected, coverage of s_1^2 and s_2^2 especially deviated from the nominal coverage rate if the true PCC was large (i.e., $\rho = 0.7071$) and yielded coverage rates closer to 0.95 if the true PCC was closer to zero (i.e., $\rho = 0.1104$). To conclude, these results show that meta-analyzing Fisher's z transformed PCCs had better statistical properties than meta-analyzing PCCs for the conditions in this simulation study.

TABLE 1 Results of reproducing the simulation study of Stanley and Doucouliagos.[5]

Design		Bias			RMSE			Coverage		
ρ	n	s_1^2	s_2^2	Fisher's z	s_1^2	s_2^2	Fisher's z	s_1^2	s_2^2	Fisher's z
0.7071	25	0.0456	0.0236	**0.0079**	0.0480	0.0280	**0.0170**	0.1444	0.8458	**0.9267**
0.7071	50	0.0223	0.0110	**0.0036**	0.0245	0.0151	**0.0109**	0.4112	**0.9440**	0.9419
0.7071	100	0.0111	0.0054	**0.0018**	0.0133	0.0090	**0.0075**	0.6601	0.9750	**0.9469**
0.7071	200	0.0054	0.0026	**0.0008**	0.0074	0.0057	**0.0051**	0.8172	0.9869	**0.9557**
0.7071	400	0.0028	0.0013	**0.0005**	0.0045	0.0038	**0.0036**	0.8839	0.9911	**0.9532**
0.3162	25	0.0351	0.0177	**0.0065**	0.0464	0.0338	**0.0284**	0.7302	0.8985	**0.9501**
0.3162	50	0.0179	0.0083	**0.0029**	0.0265	0.0208	**0.0189**	0.8336	0.9373	**0.9557**
0.3162	100	0.0088	0.0039	**0.0013**	0.0158	0.0135	**0.0129**	0.8992	**0.9510**	0.9564
0.3162	200	0.0045	0.0021	**0.0008**	0.0102	0.0093	**0.0091**	0.9266	**0.9558**	0.9564
0.3162	400	0.0023	0.0011	**0.0004**	0.0068	0.0065	**0.0064**	**0.9419**	0.9606	**0.9591**
0.1104	25	0.0127	0.0059	**0.0021**	0.0362	0.0324	**0.0309**	0.9067	0.9367	**0.9533**
0.1104	50	0.0073	0.0034	**0.0016**	0.0228	0.0212	**0.0206**	0.9283	**0.9502**	0.9606
0.1104	100	0.0031	0.0011	**0.0002**	0.0149	0.0144	**0.0142**	**0.9465**	0.9546	0.9585
0.1104	200	0.0017	0.0007	**0.0002**	0.0102	0.0100	**0.0099**	**0.9506**	0.9557	0.9564
0.1104	400	0.0007	0.0002	**0.0000**	0.0072	0.0071	**0.0071**	**0.9521**	0.9542	0.9548

Note: Values in bold indicate the approach with the least biased, lowest root mean square error (RMSE), or coverage rate that was closest to the nominal coverage rate of 0.95 for a particular condition.

Abbreviations: Fisher's z, meta-analysis based on Fisher's z transformed partial correlation coefficients and sampling variance estimated with Equation (4).; s_1^2, sampling variance estimated with Equation (1); s_2^2, sampling variance estimated with Equation (2).

4 | DISCUSSION

PCCs are frequently meta-analyzed without applying the Fisher's z transformation. Assumptions of the meta-analysis model are by definition violated when PCCs are meta-analyzed, because the sampling distribution of each primary study's effect size does not follow a normal distribution and the sampling variance cannot assumed to be known as it is a function of the PCC. An alternative for meta-analyzing PCCs is to apply Fisher's z transformation. Fisher's z transformed PCCs approximately follow a normal distribution and its sampling variance is independent of the PCC, so meta-analyzing Fisher's z transformed PCCs is more in line with the assumptions of the meta-analysis model.

I reproduced the simulation study of S&D and show that meta-analyses based on Fisher's z transformed PCCs are less biased and have lower RMSE than meta-analyses based on PCCs for all included conditions. Moreover, the meta-analyses based on Fisher's z transformed PCCs also yielded coverage rates of the confidence intervals that were close to the nominal coverage rate. Hence, meta-analyzing Fisher's z transformed PCCs are a viable alternative for meta-analyzing PCCs. I recommend to accompany any meta-analysis based on PCCs with one using Fisher's z transformed PCCs to study the robustness of the results. This is especially valuable if the true PCC is expected to be substantially different from zero or between-study variance in true effect sizes is expected to be large. In these cases, large PCCs in the primary studies are likely to be observed which is less in line with the assumptions of the meta-analysis model.

There is, however, debate about whether the Fisher's z transformation should be applied to Pearson correlation coefficients,[30–34] and this likely generalizes to PCCs as well given the close similarities between the two effect size measures. One of the main points of the debate is how to simulate from the distribution of true effect sizes and what the mean of this distribution is. The difficulty here is that true correlations can be outside the parameter space (smaller than -1 or larger than 1). Proposed solutions for this are simulating Fisher's z transformed Pearson correlation coefficients as true effect sizes, resampling a true Pearson correlation coefficient if it is outside the parameter space, and setting true Pearson correlation coefficients outside the parameter space to highly negative or positive correlations.[35–37] The differences in statistical properties of meta-analyses based on untransformed or Fisher's z transformed Pearson correlation coefficients depend on the procedure for simulating the true correlations. Future research is needed to sort out when meta-analyzing untransformed or transformed Pearson correlation coefficients/PCCs is preferred.

Future research is also needed to study the statistical properties of methods to test and correct for small-study effects when PCCs are the effect size measure of interest. Examples of these methods are Egger's test[38] (a.k.a. funnel plot asymmetry test [FAT]) and PET-PEESE.[39] These methods include the (square root of the) sampling variances in a meta-regression model to test or correct for a relationship between the effect size and the precision of the primary studies. Publication bias is one out of many potential causes of small-study effects (see Egger et al.[38] and Sterne et al.[40] for an overview). The Type-I error rate of Egger's test will be inflated and PET-PEESE is biased[7] if PCCs are meta-analyzed, because of the dependence between the PCCs and their sampling variances. Hence, methods to test and correct for small-study effects are recommended to be applied using Fisher's z transformed PCCs, because the methods are then not affected by the sampling variance being a function of the Fisher's z transformed PCC. This issue has also been noted for other effect size measures such as Cohen's d, Hedges' g, log odds ratio[40–43] and modifications of Egger's test have been proposed such that there is no relationship between the effect size and sampling variance.[44–46]

To summarize, I illustrated that meta-analyzing Fisher's z transformed PCCs is a viable alternative to meta-analyzing PCCs. Meta-analyzing Fisher's z transformed PCCs had better statistical properties using the simulation study design of S&D. Moreover, it is more in line with the assumptions of the meta-analysis model than when meta-analyzing PCCs. I recommend to always accompany a meta-analysis based on PCCs with one using Fisher's z transformed PCCs to study the robustness of the results.

AUTHOR CONTRIBUTIONS

Robbie C. M. van Aert: Conceptualization; investigation; writing – original draft; methodology; writing – review and editing; project administration.

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CONFLICT OF INTEREST STATEMENT

The author declares no conflict of interest.

DATA AVAILABILITY STATEMENT

R code of the simulation study is available at https://osf.io/ubqfg.

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ENDNOTE

[1] One could disagree with some of the decisions that were made in the design of the simulation study of S&D. For example, S&D generated the data using the equal-effect meta-analysis model in the simulation study but analyzed these data with the random-effects meta-analysis model. S&D also used the DerSimonian and Laird estimator for estimating the between-study variance in true effect size and not the nowadays recommended restricted maximum likelihood or Paule–Mandel/empirical Bayes estimators.[18–20] When studying the coverage in the context of a random-effects meta-analysis as S&D did, it is also good practice to compute confidence intervals using the Knapp–Hartung/Sidik-Jonkman adjustment.[21–24] This adjustment makes less strong assumptions than the random-effects meta-analysis model with respect to whether the sampling variances and between-study variance are known and yields more accurate coverage rates in simulation studies.[25–28] Nevertheless, I decided to exactly reproduce the simulation study by S&D to allow for a direct comparison between the results reported in S&D and in this paper.

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