Thank you for sharing the blog post with us and for the opportunity to address your points in this response.

Your blog post concerns an issue that is not the primary focus of our meta-analysis. As outlined in our pre-registration, our project aimed to examine the *moderators* of the ability to eliminate the effects of misinformation rather than average effects.

We prepared a detailed response to a similar comment raised by other researchers, which will be published soon. We will provide you with a link as soon as it is available. In the meantime, however, we would like to clarify that, technically, we did not "average" the correction and misinformation persistence effects to derive the debunking effects. These were integrated using well-established multivariate methods (Becker, 2000; Hedges et al., 2010).

More importantly, in your post, the terms "correction" and "debunking" are mentioned as if they are synonymous. However, as we have explained in prior correspondence, in our paper, these terms have distinct technical meanings defined in the methods section. The "correction effect" is the difference in the ratings between the misinformation-only group and the correction group (between-subjects design) or the difference between the ratings obtained *after* the receipt of the misinformation and *after* correcting the misinformation (within-subjects design). The "misinformation-persistence effect" is the difference in the ratings of the correction group and the control group (between-subjects design) or the difference in the ratings obtained *before* the receipt of the misinformation and *after* correcting the misinformation (within-subjects design). The "debunking effect" integrates the correction effect and the reverse of the misinformation-persistence effect through a multivariate approach. When we discuss the "debunking effect" as nonsignificant, we do not imply that the "correction effect" is not significant. (We do note, however, that the *correction* effect is weaker than in other contexts.)

We appreciate your comments regarding the inclusion of two different effect sizes in our analyses. Researchers conduct meta-analyses to synthesize quantitative evidence with different measures that are standardized in the synthesis (Becker, 2000; Gleser & Olkin, 2009; Hedges et al., 2010; Jackson et al., 2011; Mavridis et al., 2016; Riley et al., 2017). The key consideration is determining which effects best represent a body of research and contribute meaningfully to the question at hand. In our case, the two effects we integrated reflect our question and have opposite publication bias shapes. As a result, we believe that the combination of the effects improves the validity of the results relative to focusing on the more biased correction effect. In fact, we did not combine the effects in prior work and were unable to fully resolve their bias.

We submitted a correction based on checks and recalculations of effect sizes, which is in the process of being published. The updated dataset again indicated a non-significant debunking effect, with $d = 0.11$ and *95% CI* [−0.04 to 0.26] (the correction effect: $d = 0.39$, *95% CI* [0.28 to 0.50] and the reverse of the misinformation-persistence effect: $d = -0.34$, *95% CI* [-0.55 to -0.12], using the hierarchical-effects model.) This finding highlights the ongoing challenges in fully falsifying science misinformation due to the joint impact of the corrections and the persistence of misinformation. However, the estimated mean effect size was not and should not be interpreted as an indication that corrections have no success in this domain, just that they do not fare well against the misinformation.

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