**Supplementary File S2**

**Dissemination Bias Detection Methods**

First, we visually inspected contour-enhanced funnel plots (Light et al., 1984) for asymmetry. However, due to partial effect size dependencies, this represents a rather noisy illustration of effect distributions in multilevel models. Second, we ran a trim and fill analysis, which provides a formal assessment of funnel plot asymmetry (Duval and Tweedie, 2000) and can be interpreted in terms of a sensitivity analysis (see Siegel et al., 2022), but does not account for primary effect size dependencies. Third, we used two variants of Egger’s regression test (Egger et al., 1997) which have been adapted to accommodate multilevel modeling. In two-level meta-analyses, Egger’s regression is done by regressing effect sizes on their precision estimates which are considered to be indicative of funnel plot asymmetry, if significant at *p* < .10 (Sterne and Egger, 2005). Because Eggers’s method is a regression-based method, it can be readily used in multilevel approaches. On the one hand, Egger’s regression can be combined with robust variance estimation for dependent data using sandwich estimators (Rodgers and Pustejovsky, 2020). On the other hand, sandwich estimation can be combined with multilevel modeling (MLMA) of Egger’s regression which has been shown to perform favorably in terms of type I error probability, although bias detection power is rather small (Van den Noorgate et al., 2013). Fourth, we used a three-parameter selection approach which aims at estimating potential bias by specifying *p*-value-based weight functions that should be unrelated to effect strengths when there is no bias. Simulation studies showed good performance of this method to detect bias in terms of selective reporting in multilevel modeling, despite somewhat inflated type I error rates (Rodgers and Pustejovsky, 2020). In accordance with common standards in analytic practices, regression-based bias analyses will be considered to be indicative of bias at an alpha level of .10 (Siegel et al., 2022).

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