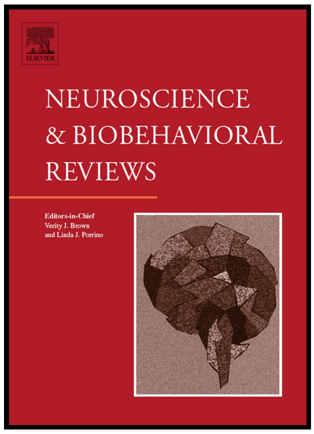
Journal Pre-proof



Publication bias casts doubt on implicit processing in inattentional blindness

Alexandre de Pontes Nobre, Gabriela Mueller de Melo, David R. Shanks

PII: S0149-7634(22)00264-0

DOI: https://doi.org/10.1016/j.neubiorev.2022.104775

Reference: NBR104775

To appear in: *Neuroscience and Biobehavioral Reviews*
Revised date: 12 June 2022
Accepted date: 8

Please cite this article as: Alexandre de Pontes Nobre, Gabriela Mueller de Melo and David R. Shanks, Publication bias casts doubt on implicit processing in inattentional blindness, *Neuroscience and Biobehavioral Reviews,* (2022) doi:https://doi.org/10.1016/j.neubiorev.2022.104775

This is a PDF file of an article that has undergone enhancements after acceptance, such as the addition of a cover page and metadata, and formatting for readability, but it is not yet the definitive version of record. This version will undergo additional copyediting, typesetting and review before it is published in its final form, but we are providing this version to give early visibility of the article. Please note that, during the production process, errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

© 2022 Published by Elsevier.

Publication bias casts doubt on implicit processing in inattentional blindness

Alexandre de Pontes Nobre[a], Gabriela Mueller de Melo[b], and David R. Shanks[c]

[a] Institute of Psychology, Federal University of Rio Grande do Sul. Ramiro Barcelos 2600, 90035-003, Porto Alegre, Rio Grande do Sul, Brazil.

[b] Institute of Biosciences, University of São Paulo (USP), Rua do Matão, tv. 14, n° 321, Cidade Universitária, 05508-090, São Paulo - SP, Brazil.

[c] Division of Psychology and Language Sciences, University College London, 26 Bedford Way, London WC1H 0AP, UK

Journal Pre-proof

We have no known conflicts of interest to disclose. This research was funded by grant 2020/09284-5 from the São Paulo Research Foundation (FAPESP) to G. M. de Melo and grant ES/S014616/1 from the United Kingdom Economic and Social Research Council to D. Shanks. The funding sources had no involvement in the study. Code for the analyses reported in this article is available at https://osf.io/cyk5e/.

Correspondence concerning this article should be addressed to Alexandre de Pontes Nobre. Email: alpnobre@gmail.com. Telephone: 55 51 3308 5341.

Abstract

Two recent meta-analyses on inattentional blindness (Kreitz, Pugnaghi, & Memmert, 2020; Nobre et al., 2020) concluded that objects can be processed implicitly even when attention is directed elsewhere. However, signs of publication bias are evident in both of these meta-analyses. Here, we employed multiple tools to correct for publication bias in the data aggregated in those meta-analyses. Analyses using the Precision-Effect Test (PET) and robust Bayesian meta-analysis (RoBMA) suggest that the estimates in the original meta-analyses were inflated, together with strong evidence of publication bias. Indeed, the data are consistent with no overall implicit effects. We suggest that more evidence, particularly from well-powered pre-registered experiments, is needed before solid conclusions can be drawn regarding implicit processing during inattentional blindness.

Keyword

meta-analysis; Inattentional blindness; implicit processing; publication bias.

Journal Pre-proof

Publication bias casts doubt on implicit processing in inattentional blindness

Research on inattentional blindness has established the remarkable finding that salient objects in plain view can be unseen if attention is engaged elsewhere. Two recent meta-analyses (Kreitz, Pugnaghi, & Memmert, 2020; Nobre et al., 2020) reviewed evidence that such unseen objects are nonetheless sometimes processed implicitly – for instance, affecting response times or accuracy in a separate task. Across k = 59 experiments, Nobre et al. found a medium-sized average meta-analytic implicit effect of r = .33, 95 % confidence interval (CI) [.21, .45], while Kreitz et al. (who analyzed data from their own research group) found a smaller effect, k = 16, Cohen's d = 0.211 [0.106, 0.316]. Nobre et al.'s (2020) dataset included a subset (k = 14 studies employing visual stimuli) of those aggregated by Kreitz et al. (2020).

At face value these meta-analyses, combining data across 3,464 participants, conclusively demonstrate that unseen objects are processed implicitly. We argue here, however, that there are signs of severe publication bias in this field and that when cutting-edge techniques are employed to correct the above estimates for publication bias, the true average effect size is approximately zero.

While Kreitz et al. (2020) did not discuss publication bias in their meta-analysis, Nobre et al. (2020) examined a funnel-plot for the effect sizes (see Figure 1) and duly noted the presence of publication bias, which they corrected for using the Trim-and-Fill method (Duval & Tweedie, 2000). After this correction, they still obtained a significant, albeit smaller, overall effect (r = .18), indicating that implicit processing occurred during inattentional blindness. However, recent simulation studies (Carter et al., 2019) suggest that, in the prevailing conditions of the meta-analysis, the Trim-and-Fill method has a very high false positive rate (the rate at which a method falsely concludes that there is a non-zero effect when the true effect is zero). Therefore, we conducted alternative analyses (using methods that were not available when the original meta-analyses were conducted) to obtain a better estimate of the overall effect size after correcting for publication bias.

Assessing publication bias in the published meta-analyses

Using Carter et al.'s (2019) MetaExplorer application (http://shinyapps.org/apps/metaExplorer/), we estimated false positive rates to assess the performance of five different methods: standard random-effects meta-analysis, Trim-and-Fill, the Precision-Effect (PET) and Precision-Effect Estimate with Standard Errors (PEESE) tests, and a 3-parameter selection model (3PSM; see Carter et al. for further details about these methods). We adopted a maximum acceptable false positive rate of 20% as the threshold to decide whether each method was acceptable or not.

Journal Pre-proof

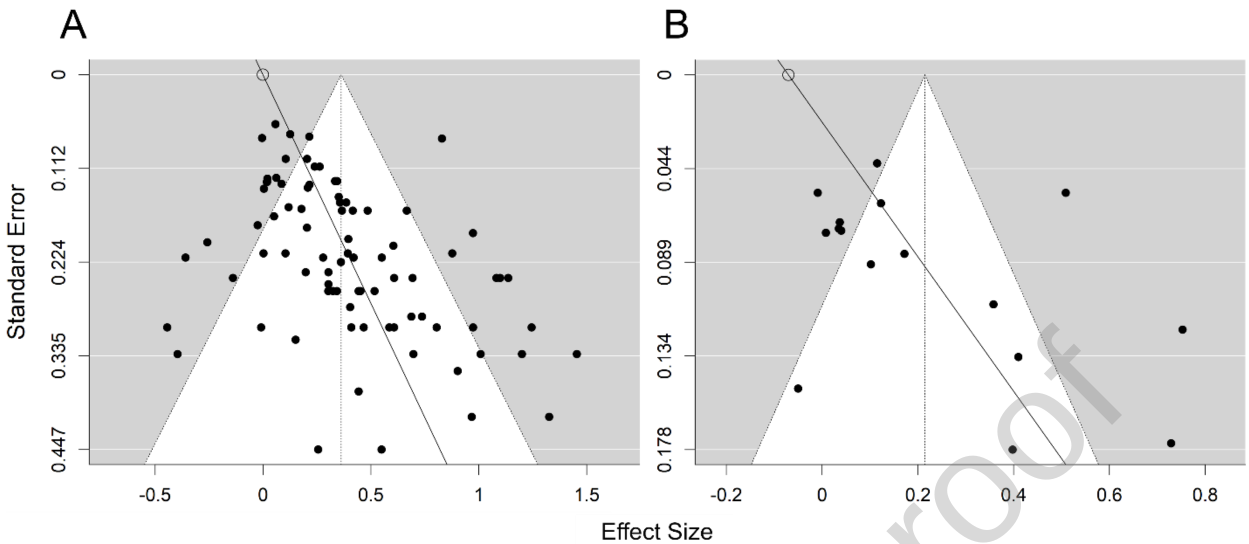


Figure 1. Funnel plots for the datasets analyzed. A: Funnel plot for the data of Nobre et al. (2020), in correlation values (*r*). B: Funnel plot for the data of Kreitz et al. (2020), in Cohen's *d* values. Open circles are PET estimates.

The parameters used in the simulations were selected as follows. For Nobre et al.'s (2020) dataset, we assumed medium severity of publication bias and a medium level of questionable research practices (QRPs) environment (see Carter et al., 2019, for definitions of these parameters). We examined results for two levels of heterogeneity: medium ($\tau = 0.2$) and high ($\tau = 0.4$). Under these conditions the Trim-and-Fill method employed by Nobre et al. (2020) has a false positive rate over 80% and is clearly inadequate as a correction method. However, whereas the simulation showed lower false positive rates for both PET and 3PSM (see Tables S1 and S2 in the Supplementary Information), for PEESE we obtained an unacceptably high false positive rate (72% for medium heterogeneity, 53% for high heterogeneity), so we removed PEESE from further analyses.

Journal Pre-proof

Table 1 shows the estimates and confidence intervals for the analysis reported by Nobre et al. (2020) as well as PET and 3PSM, using correlation coefficients as effect sizes. The table also includes the Trim-and-Fill estimate, even though the above analysis suggests that it is inappropriate in this context. The estimate is included to confirm that we reproduce the same value as Nobre et al. (2020). PET showed an influence of standard error on effect size ($p < .001$). The bias-corrected estimate computed by PET is close to 0 (Table 1) and is not significant in the model ($p = .99$). Thus, when a bias-correcting method is employed that is less prone to false positives, the overall effect disappears. On the other hand, 3PSM yielded an estimate close to the one obtained using a random-effects model. A likelihood ratio test comparing the fit of the adjusted model to that of the random-effects model was not significant, χ^2 (1) = 0.09, $p = .76$, indicating that 3PSM does not improve the fit compared to the original model, revealing no publication bias.

Journal Pre-proof

Table 1. Estimates, confidence intervals and outcome of publication bias assessment by method.

Bias correction method	**Estimate**	**95% CI**	**Publication bias**
	Nobre et al. (2020)		
RE	.33	[.21, .45]	-
Trim-and-Fill	.18	[.08, .28]	Yes
PET	-.01	[-.17, .17]	Yes
3PSM	.35	[.22, .46]	No
RoBMA	.037	[-.09, .42]	Yes

Kreitz et al. (2020)			
RE	.21	[.10, .33]	-
Trim-and-Fill	.21	[.10, .33]	No
PET	-.07	[-.34, .20]	Yes
3PSM	.20	[.02, .38]	No
RoBMA	.13	[-.20, .68]	Yes

Note: RE = Random-Effects model; PET = Precision-Effect Test; 3PSM = 3-Parameter Selection Model; RoBMA = Robust Bayesian Meta-Analysis. Effect sizes estimates are correlation coefficients for Nobre et al. (2020) and Cohen's *d* values for Kreitz et al. (2020).

Journal Pre-proof

Lastly, we employed the recently developed robust Bayesian meta-analysis approach (RoBMA; Bartoš, Maier, Quintana, & Wagenmakers, 2022; Maier, Bartoš, & Wagenmakers, 2022). RoBMA uses Bayesian model-averaging to combine estimates from multiple models — including PET, PEESE and selection models — both with and without publication bias. Each method is fit to the data and then the estimated effect is computed by weighting each of them by its likelihood, given the data. This method computes Bayes factors to quantify the evidence for the presence or absence of an effect as well as of publication bias. RoBMA has been shown to be superior to other bias-correction methods via several simulation studies (Bartoš, Maier, Quintana, & Wagenmakers, 2022; Maier et al., 2022). We fit RoBMA assuming equal prior probabilities across model types. Bayes factors indicated moderate evidence against the presence of an overall effect of implicit processing (BF_{10} = 0.30) and extreme evidence for publication bias (BF_{10} = 3303.90). These results suggest that the overall effect Nobre et al. (2020) reported might be distorted by publication bias in the inattentional blindness literature.

For Kreitz et al.'s (2020) dataset, we ran the Carter et al. (2019) simulation assuming high heterogeneity ($\tau = 0.4$) and a medium level of QRPs. We simulated two levels of publication bias, medium and high. Again, Trim-and-Fill shows a high false positive rate (30%, above our cutoff point of 20%). PEESE also returned a high false positive rate, so we removed it from further analysis.

Table 1 displays the results of those analyses. Whereas RE, Trim-and-Fill, and 3PSM provide confidence intervals that do not include zero, PET shows a wide confidence interval consistent with an effect size of zero. For publication bias assessment, results were mixed: among frequentist models, only PET found publication bias. RoBMA also showed evidence for publication bias ($BF_{10} = 10.11$), as well as moderate evidence against an effect ($BF_{10} = 0.32$). Thus, the results again suggest it is possible that the true average effect is close to zero when corrected for publication bias.

Turning to heterogeneity, Nobre et al.'s (2020) meta-analysis revealed considerable heterogeneity among effect sizes, which was partly explained by the presence of moderators. For this reason, we conducted the same analyses within subgroups defined by those moderators (see Supplemental Information). Although these analyses found that the evidence for publication bias differs among subgroups, in none was the effect size significantly different from zero.

Discussion

In sum, the analyses reported here provide considerable evidence that the results of both Nobre et al. (2020) and Kreitz et al. (2020) were distorted by publication bias. In both meta-analyses, correcting for this bias with PET and RoBMA yields effects sizes that are smaller than those originally reported, and not significantly greater than zero. Moreover, the high

Journal Pre-proof

heterogeneity in both datasets, as well as the characteristics of several of the studies included in those meta-analyses (small *N*s, use of multiple measures of implicit processing, selective reporting of results) make the results even more difficult to interpret.

It is important to emphasize that the bias-correction methods employed here only perform satisfactorily under certain assumptions. As Carter et al.'s (2019) simulations demonstrated, these methods may underperform in some settings, and we selected a subset of methods for our analysis — for example, including PET but not PEESE — based on how they are expected to perform according to the simulations. Nevertheless, evaluating the performance of these methods is a complex issue, and our results should be read as suggestive rather than conclusive.

We should note that two of us are authors of one the meta-analysis examined here (Nobre et al., 2020). Research on bias correction is rapidly developing, and important improvements in this field have occurred since the publication of our previous review. The difference between our conclusions here and those of Nobre et al. (2020) is due to the availability of cutting-edge bias-detection methods and growing recognition of the need to employ them in interpreting meta-analyses (e.g., Bartoš, Maier, Quintana, & Wagenmakers, 2022; Carter et al., 2019; Maier et al., 2022; Stanley et al., 2021).

Importantly, both Nobre et al. (2020) and Kreitz et al. (2020) included only a few pre-registered experiments (10 out of 59 and 6 out of 16, respectively). In each review, a little over half of the pre-registered studies (6/10 for Nobre et al., 2020; 4/7 for Kreitz et al., 2020) provided results that support the hypothesis of implicit processing during inattentional blindness. Fitting a random-effects model to the subset of pre-registered experiments in Nobre et al. (2020) shows an overall effect size of $r = .22$ that is significantly different from zero ($t = 2.46$, $p = .03$). For pre-registered experiments in Kreitz et al. (2020), an effect size of $d = .32$ was found, which was also

Journal Pre-proof

significant ($z = 2.11$, $p = .03$). However, the resulting sample of pre-registered experiments in each meta-analysis is small, so these results should be interpreted with care.

Implicit processing is a field where the lack of reproducible results and publication bias is widely found, as in the case of priming studies which could not be reproduced in the last decade (e.g., O'Donnell et al., 2018; Rohrer, Pashler, & Harris, 2015; Shanks, et al., 2015). Our results demonstrate how the application of bias-detection methods may substantially change the conclusions of a meta-analysis. This approach has implications for other areas within psychology, since more than half of all meta-analyses in psychology probably overestimate the evidence for the presence of effects (Bartoš, Maier, Shanks, et al., 2022).

Our results suggest that the existence of implicit processing during inattentional blindness is unproven and questionable. Thus, although further meta-analyses may provide powerful conclusions on this question, the field may benefit from experiments that conform to more recent methodological guidelines for reproducibility and transparency, such as multi-lab approaches. In particular, to reach more solid conclusions on effects of implicit processing during inattentional blindness, we emphasize a need for pre-registered experiments, to minimize the possibility of publication bias; and further research aimed at understanding the roots of the heterogeneity evident amongst these effects.

Journal Pre-proof

References

Bartoš, F., Maier, M., Shanks, D., Stanley, T. D., Sladekova, M., & Wagenmakers, E. (2022, June 1). *Meta-Analyses in Psychology Often Overestimate Evidence for and Size of Effects*. https://doi.org/10.31234/osf.io/tkmpc

Bartoš, F., Maier, M., Quintana, D. S., & Wagenmakers, E.-J. (2022). Adjusting for publication bias in JASP & R: Selection models, PET-PEESE, and robust Bayesian meta-analysis. *Advances in Methods and Practices in Psychological Science*.

Carter, E. C., Schönbrodt, F. D., Gervais, W. M., & Hilgard, J. (2019). Correcting for bias in psychology: A comparison of meta-analytic methods. *Advances in Methods and Practices in Psychological Science*, *2*(2), 115–144. https://doi.org/10.1177/2515245919847196

Duval, S., & Tweedie, R. (2000). Trim and fill: A simple funnel-plot-based method of testing and adjusting for publication bias in meta-analysis. *Biometrics*, *56*(2), 455–463. https://doi.org/10.1111/j.0006-341X.2000.00455.x

Kreitz, C., Pugnaghi, G., & Memmert, D. (2020). Guessing right: Preconscious processing in inattentional blindness. *Quarterly Journal of Experimental Psychology (2006)*, *73*(7), 1055–1065. https://doi.org/10.1177/1747021820911324

Maier, M., Bartoš, F., & Wagenmakers, E.-J. (2022). Robust Bayesian meta-analysis: Addressing publication bias with model-averaging. *Psychological Bulletin*.

Journal Pre-proof

Nobre, A. de P., de Melo, G. M., Gauer, G., & Wagemans, J. (2020). Implicit processing during inattentional blindness: A systematic review and meta-analysis. *Neuroscience & Biobehavioral Reviews*, *119*, 355–375. https://doi.org/10.1016/j.neubiorev.2020.10.005

O'Donnell, M., Nelson, L. D., Ackermann, E. Aczel, B., Akhtar, A. Aldrovandi, S., Alshaif, N. Andringa, R., Aveyard, M. Babincak, P., Balatekin, N., Baldwin, S., Banik, G., Baskin, E., Bell, R., Bialobrzeska, O., Birt, A., Boot, W. R., Braithwaite, S. R., … Zrubka, M. (2018). Registered replication report: Dijksterhuis & van Knippenberg (1998). *Perspectives on Psychological Science, 13,* 268-294.

Rohrer, D., Pashler, H., & Harris, C. R. (2015). Do subtle reminders of money change people's political views? *Journal of Experimental Psychology: General, 144,* e73-e85.

Shanks, D. R., Vadillo, M. A., Riedel, B., Clymo, A., Govind, S., Hickin, N., Tamman, A. J. F., & Puhlmann, L. M. C. (2015). Romance, risk, and replication: Can consumer choices and risk-taking be primed by mating motives? *Journal of Experimental Psychology: General, 144*, e142-e158.

Stanley, T. D., Doucouliagos, H., Ioannidis, J. P. A., & Carter, E. C. (2021). Detecting publication selection bias through excess statistical significance. *Research Synthesis Methods*, *12*(6), 776–795. https://doi.org/https://doi.org/10.1002/jrsm.1512

Journal Pre-proof