

**Dear Dr. Zoltan Dienes,**

**Thank you for allowing us to submit the revised version of our Stage-1 manuscript titled “Do task-irrelevant cross-modal statistical regularities induce distractor suppression in visual search?” to PCI RR.**

**We would like to thank you for providing suggestions to improve the quality of the manuscript. Below you can find our response to your suggestions/comments in bold.**

**We have submitted the revised Stage-1 Registered report (file name: “Registered\_Report\_Stage-1\_Proposal\_v4.pdf”). We have also uploaded a PDF document indicating modifications in Tracked changes.**

**We look forward to your comments.**

**With kind regards,  
Kishore Kumar Jagini (on behalf of authors)**

### **Recommender**

Let me just recap. For your previous power analysis you used  $d = 0.45$  because it was somewhat smaller than the  $d = .60$  of a previous study. In the last submission, you justify the minimal effect somewhat better by using the lower limit of a CI for a relevant effect from a previous study. For your first hypothesis you take the lower bound of a 60% CI of previous study to get  $d = 0.42$ . You explain you used a 60% CI because your practical maximum N is 85. For the second hypothesis you use a 95% CI of a previous study relevant to that effect which gives a  $d = 0.41$ , so consistent with your practical maximum N.

So what you have done is retrofitted the heuristic by choosing a % for the CI to fit what you could do practically. That is, the real heuristic that you used was to fit to your practical limit (which is scientifically irrelevant). What you need to do is work the other way round - start from the scientific context, and what you can practically do is either sufficient to address the scientific problem or not. If it is not, you would say up front that a non-significant result would not count against the hypothesis of a scientifically relevant effect. Now the % used for the CI is also arbitrary. But there is no scientific reason on the table for why the % should be different for the different problems. Also it is clear that a 60% CI rules out too little in terms of finding the smallest plausible value. I suggest you use a 80% CI for both problems; find the lower limit, and work out your power for both hypotheses with respect to that.

One further point that need not entail any revision to the current manuscript but should be brought up in your discussion if not. Your test of awareness is a forced choice test and does not separate out objective and subjective thresholds. On two common theories of consciousness (higher order and global workspace) unconscious knowledge would allow above chance performance on your test. On another theory, (recurrent processing) your test does measure conscious processing. (See <https://osf.io/mzx6t/> ) Thus, finding that the knowledge was above chance on your awareness test would only indicate conscious knowledge given some but not other theories of consciousness.

**Response: Thank you for suggestions. We revised the manuscript to include appropriate justification for effect sizes for each proposed hypothesis test. Relying on the effect size from the previous study at the face value for an a priori power analysis is not recommended, as this might lead to underpowered studies (Dienes, 2021; Perugini et al., 2014). To guard against the underpowered study, we determined the smallest effect size of interest as the lower limit of 80% confidence interval (CI) for the effect size by following the advice of Perugini et al. (2014). Using the determined smallest effect size of interest for each test, we conducted an a priori power analysis. The lower CI limits were calculated using the Shiny R based web app ([https://designingexperiments.shinyapps.io/ci\\_smd/](https://designingexperiments.shinyapps.io/ci_smd/)), and the sample size calculations were done by G\*Power 3.1 software. The screenshots of these calculations attached in the appendix below. Please see the uploaded PDF document indicating these revisions in Tracked changes.**

## Appendix:

Screenshots of Shiny R web app for estimating confidence interval for the effect size (standardised mean difference). Web app link: [https://designingexperiments.shinyapps.io/ci\\_smd/](https://designingexperiments.shinyapps.io/ci_smd/)

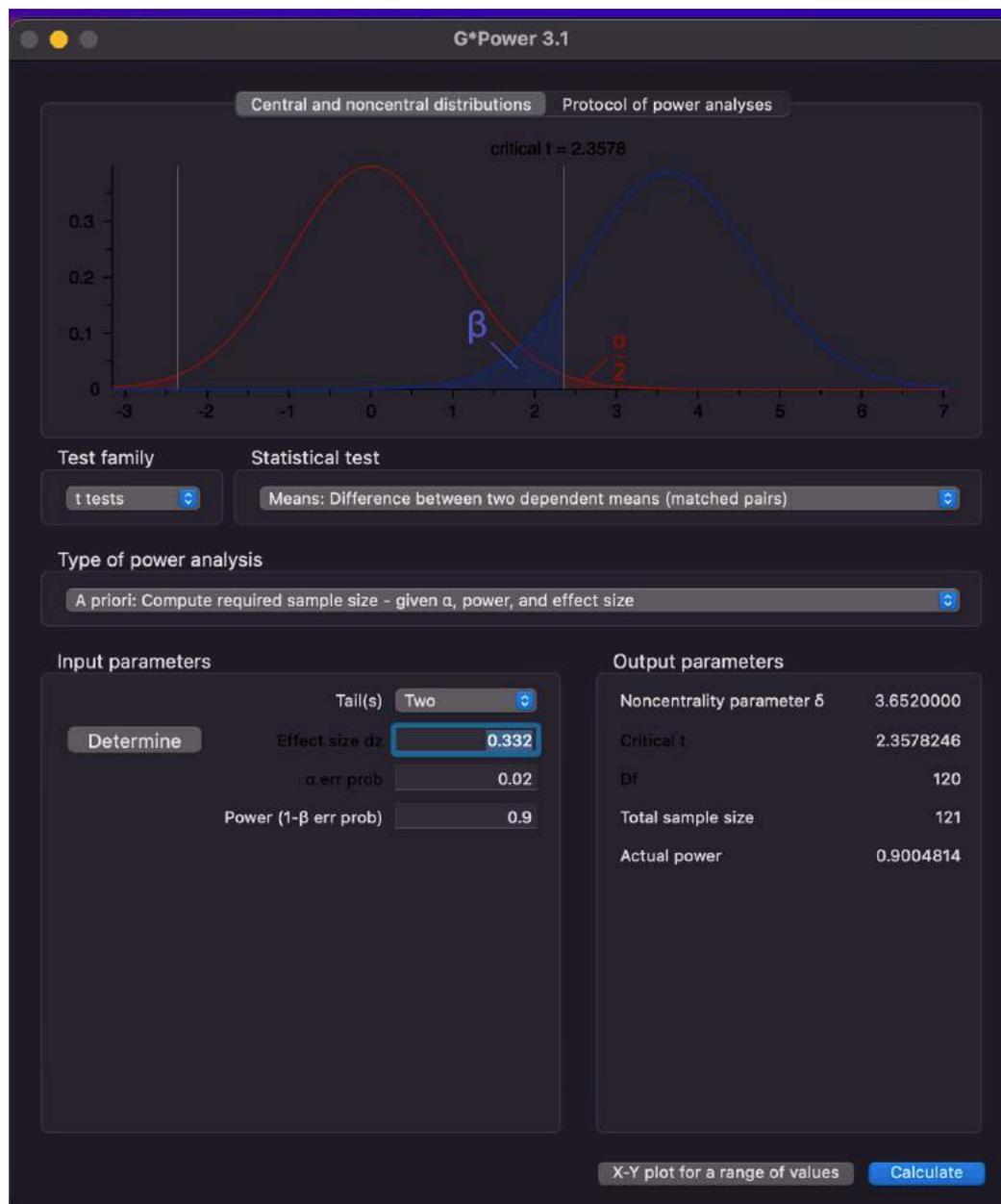
The screenshot shows the Shiny R web app interface for calculating a confidence interval for the population standardized mean difference. The title is "Confidence Interval for the Population Standardized Mean Difference". On the left, there are four input fields: "Sample size for group 1" (48), "Sample size for group 2" (48), "Standardized mean difference" (0.602), and "Confidence level" (0.80). On the right, a box displays the calculated values: Lower.Conf.Limit.smd (0.3328536), smd (0.602), and Upper.Conf.Limit.smd (0.867979). Below the values, a paragraph explains that the two-sided confidence interval is calculated using the `ci.smd()` function from the MBESS R package, and mentions the Shiny app's association with the book "Designing Experiments and Analyzing Data: A Model Comparison Perspective (3rd edition)" by DesigningExperiments.Com.

| Parameter            | Value     |
|----------------------|-----------|
| Lower.Conf.Limit.smd | 0.3328536 |
| smd                  | 0.602     |
| Upper.Conf.Limit.smd | 0.867979  |

The screenshot shows the Shiny R web app interface for calculating a confidence interval for the population standardized mean difference. The title is "Confidence Interval for the Population Standardized Mean Difference". On the left, there are four input fields: "Sample size for group 1" (166), "Sample size for group 2" (166), "Standardized mean difference" (0.57), and "Confidence level" (0.80). On the right, a box displays the calculated values: Lower.Conf.Limit.smd (0.4260606), smd (0.57), and Upper.Conf.Limit.smd (0.7130834). Below the values, a paragraph explains that the two-sided confidence interval is calculated using the `ci.smd()` function from the MBESS R package, and mentions the Shiny app's association with the book "Designing Experiments and Analyzing Data: A Model Comparison Perspective (3rd edition)" by DesigningExperiments.Com.

| Parameter            | Value     |
|----------------------|-----------|
| Lower.Conf.Limit.smd | 0.4260606 |
| smd                  | 0.57      |
| Upper.Conf.Limit.smd | 0.7130834 |

### Screenshots of power calculation using G\*Power 3.1:





## References:

Dienes, Z. (2021). Obtaining Evidence for No Effect. *Collabra: Psychology*, 7(1).  
<https://doi.org/10.1525/collabra.28202>

Perugini, M., Gallucci, M., & Costantini, G. (2014). Safeguard Power as a Protection Against Imprecise Power Estimates. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science*, 9(3), 319–332.  
<https://doi.org/10.1177/1745691614528519>