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Shlomo S. Sawilowsky
Wayne State University, shlomo@wayne.edu

Jina S. Yoon
Wayne State University

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Shlomo S. Sawilowsky
Educational Evaluation and Research
College of Education
Wayne State University

Jina S. Yoon
Educational Psychology
College of Education
Wayne State University

Trivials are effect sizes associated with statistically non-significant results. Trivials are like Tribbles in the *Star Trek* television show. They are cute and loveable. They proliferate without limit. They probably growl at Bayesians. But they are troublesome. This brief report discusses the trouble with trivials.

Keywords: Effect size, Meta analysis

Introduction

Among various reforms suggested to the *American Educational Research Association*'s editorial policies directed at "editors, program chairs, and reviewers" (p. 28), Thompson (1996) recommended the reporting of effect sizes "regardless of whether statistical tests are or are not reported" (p. 29), "even [for] non-statistically significant effects" (1999, p. 67). Similar advice was given by Carver (1993), Hulburt (1994), Rosnow and Rosenthal (1989), and Wilkinson (1999).

Heuristic support in the form of a thought experiment designed to illustrate the concern with this suggested reform was given by Robinson and Levin (1997). They concluded that a better editorial practice is to "First convince us that a finding is not due to chance, and only then, assess how impressive it is" (p. 23).

Purpose of This Study

This study presents Monte Carlo evidence, which is more convincing than a thought experiment, to demonstrate the perils of reporting and interpreting effect sizes arising from nonstatistically significant research studies.

Shlomo S. Sawilowsky, Wayne Statue University Distinguished Faculty Fellow, is Professor and Chair, Educational Evaluation and Research, 351 College of Education, Wayne State University, Detroit, MI, 48202, e-mail: shlomo@edstat.coe.wayne.edu. His interests are in nonparametric, robust, exact, permuation, and other computer-intensive methods, especially via Fortran. Jina Yoon is Assistant Professor, Educational Psychology, College of Education, Wayne State University. Her research interests are social emotional functioning of children and adolescents, school environments, and teacher-student relationships.

Methodology

A Fortran 95 program was written to randomly draw variates from a deMoivreian (i. e., normal) distribution and then randomly assigned to two groups ($n_1 = n_2 = 10$), with the first group designated the treatment and the second the control. A two-sided two independent samples t test was conducted with nominal $\alpha = 0.05$. 10,000 repetitions were conducted.

The effect were considered (a) under the truth of the null hypothesis, and (b) for shift in location parameter, which was simulated by adding a constant "c", representing 0.52 (a moderate effect size according to Cohen, 1988). This shift was selected to produce a power of about .2 for the t test for the given sample size and α level.

Small sample size and power level were chosen to mimic applied research. A balanced layout and a theoretically normally distributed data set were chosen to demonstrate what happens under the best of circumstances with regard to layout and data distribution assumptions. Nominal α was selected at 0.05 due to Cohen (1994).

Results

The results are compiled in Table 1. The upper panel represents the various outcomes due to random numbers, where the effect size is modeled as zero. The entries were obtained by averaging the absolute value of d, given by the formula $d = (\bar{x}_t - \bar{x}_c)/s_{pooled}$, where s_{pooled} refers to the pooled estimate of σ. (The absolute value was taken because the order of $\bar{x}_t$ and $\bar{x}_c$ is arbitrary). The upper panel demonstrates the trouble with reporting and interpreting effect sizes when the results of the experiment are statistically trivial. A fail to reject decision was reached in 95% of the repetitions of the experiment. Reporting an average effect size of 0.17, which is approximately what Cohen (1988) judged to be a small effect size, is misleading because these

Table 1. Effect Sizes for $n_1 = n_2 = 10$, Gaussian Distribution, Nominal $\alpha = 0.05$.

	H_o	
	True	False
	Random Numbers	
Decision		
Fail To Reject	0.169 ± .003	n/a
	(Type I Errors)	
Reject	0.508 ± .007	n/a
	Shift = 0.52 σ	
	Power = 0.20	
		(Type II Errors)
Fail To Reject	n/a	0.180 ± .006
Reject	n/a	0.540 ± .005

effect sizes are specious. There can be no effect size because none was modeled in the data generation.

(The remaining results aren't relevant to the main pronouncement of this paper, but are presented to complete the illustration. The adverse effects of making a Type I error is demonstrated, because an average effect size of 0.51 was obtained, a medium effect size, Cohen, 1988, when in fact the true effect size is zero.

In the second case, depicted by the lower panel, one-tailed power is represented by averaging the effect sizes. As predicted by Cohen's (1988) power tables, when the false null hypothesis is rejected, the average effect size reported and interpreted is a moderate 0.54. This is a meaningful effect size to report and interpret.

However, when the t test failed to reject the false null hypothesis, the resulting calculations indicate the effect size under consideration was only 0.18. Similar results were obtained for the t test when data were drawn from nonnormally distributed data, indicating that the t test is (a) robust with respect to Type II errors, but more importantly, (b) is less powerful than competitors, such as the Wilcoxon Rank-Sum test, which would have rejected many more of these false null hypotheses.)

Conclusion

It was shown that effect sizes should not be reported or interpreted in the absence of statistical significance. As Shaver (1993) noted, even "an effect size of 1 or larger may reflect a *trivial* result" (p. 303, emphasis added). This is the trouble with trivials.

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