A systematic review of the prevalence of Null Hypothesis Significance Testing,

sample sizes, and implied statistical power in research using

the Implicit Relational Assessment Procedure (2006-2022)

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Here I provide a systematic review of published research using the Implicit Relational Assessment Procedure (IRAP). This manuscript does not perform any synthesis of the research, it merely describes the search and exclusion process of this systematic review. The publications returned by this systematic review can be used in other work that seeks to do such syntheses (e.g., reviews of methods or findings).

Two seminal articles were published in 2011 whose implications the field of psychology is still grappling with. The first, by Daryl Bem (2011), contained literally impossible results about a supposed human ability to predict the future. It was remarkable not merely in its claims but because it employed modal research practices for the field to substantiate these conclusions. A second article by Simmons and colleagues (2011), coincidentally published around the same time as Bem (2011) but without any knowledge of his paper, demonstrated how our modal research practices can easily and routinely generate statistically significant results from what is actually just noise.

The fallout from this pair of papers and many more before and since is now a matter of history for some (e.g., for personal accounts see Gelman, 2016; Spellman, 2015). But their impact has been uneven and recognition of the replication crisis as a serious issue to be reckoned with has been heterogenous, both within and between fields. It would be too easy to dismiss the crisis as specific to Social and Personality psychology when other fields employ similar research practices. Over time, recognition of these issues has spread to other areas of psychology (e.g., clinical psychology: Tackett et al., 2019) as well as a diverse range of other fields including cancer biology, economics, methodology, sociology, and philosophy (Baker & Dolgin, 2017; Boulesteix et al., 2020; Buckwalter, 2022; Gordon et al., 2020; Page et al., 2021).

These calls to take seriously the question of replicability have recently been echoed in the behavioral research communities. In an editorial for Perspectives on Behavior Science, Hantula (2019, pp. 4-5) recently characterized the situation well:

*“Despite certain metatheoretical disputes (Burgos & Killeen, 2019), behavior science, behavior analysis, and psychology have much more in common than differences. Hence the ‘replication crisis’ in psychology could well be repeated in behavior science and behavior analysis. Even if it is not, it may hold some important lessons for both scientists and practitioners.”*

Similarly, the Association for Contextual Behavioral Science’s Task force on the Strategies and Tactics of Contextual Behavioral Science Research (2021) recently announced its explicit support for Open Science principles, including data transparency and a focus on replication. As such, there is now support for the idea that behavioral science, including component fields such as Behavior Analysis and Contextual Behavioral Science, would be enhanced by examining and enhancing the transparency and replicability of its findings.

In some ways, this could be seen as an appropriate return to our roots, from which we should never have departed. To take some positive examples of our field’s history here, whereas general psychology journals have until recently rarely published replication studies (Makel et al., 2012), behavioral journals such as the Journal of Experimental Analysis of Behavior and Journal of Applied Behavior Analysis have long history of publishing them. Behavioral research also has a long history of sharing research data (i.e., trial-level single case experimental design data being presented in tables and plots). Lastly, despite being written over 60 years ago, fully one quarter of Murray Sidman’s seminal behavioral textbook *Tactics of Scientific Research* (1960) is dedicated to discussion of the needs for replication studies, their taxonomy and function, and links between replication and generalization.

## Replicability, sample size, and statistical power

Statistical power is the probability of detecting a true effect, and is synonymous with the sensitivity of a test and its False Negative Rate (Cohen, 1977). Low statistical power in original studies is a key contributor to the Replication Crisis in psychology (e.g., Asendorpf et al., 2013; Button et al., 2013; Munafò et al., 2017), with highly powered replications only obtaining the original finding in around one third of studies (depending on the definition of successful replication), and effect sizes observed in replication studies are typically only one-third the size of those in original studies (e.g., Ebersole et al., 2020; Klein et al., 2018; Open Science Collaboration, 2015). Journals that publish underpowered studies are likely to publish a greater proportion of conclusions that are false positives (Bakker et al., 2012; Ioannidis, 2005). As such, in reaction to the replication crisis in psychology, many have called for psychology research to employ higher powered tests and therefore larger sample sizes (e.g., Asendorpf et al., 2013; Button et al., 2013; Munafò et al., 2017; Wagenmakers et al., 2012).

Along with the False Positive Rate (i.e., α-level, typically < .05), statistical power is one of two key properties of inference via NHST that defines the long-run error rates of the inferences we make from data. Power is generally a less familiar concept than α level for many researchers, but it is so central to our ability to make inferences from data (Cohen, 1992).[[1]](#footnote-1) Nonetheless, for decades, statistical power remained very low in the behavioral sciences (i.e., around .46: Cohen, 1990). Additionally, research has shown that researchers’ intuitions about the statistical power implied by rules-of-thumb sample sizes are inaccurate and overestimate power (Bakker et al., 2016).

In order to assess the efficacy of this more recent call for higher power motivated by the replication crisis, on the sample sizes employed in published research, Fraley and colleagues (Fraley et al., 2022; Fraley & Vazire, 2014) quantified the median[[2]](#footnote-2) sample size employed in articles published in nine personality and social psychology journals between 2011 (arguably the start of the replication crisis) and 2019. Fraley and colleagues (2022) observed that median sample sizes, and therefore implied statistical power, have indeed increased over the last decade in social and personality psychology research, from very poor (circa .50 in 2011) to acceptable (circa .90 in 2019). In doing so, the Fraley and colleagues (Fraley et al., 2022; Fraley & Vazire, 2014) provided both a relatively simple method to assess the implied power across a body of work and a useful dataset to compare other fields against.

## The Implicit Relational Assessment Procedure (IRAP)

The Implicit Relational Assessment Procedure (IRAP: Barnes-Holmes et al., 2006) is a reaction-time based task used variously as a measure of implicit attitudes in implicit social cognition research and a measure of the strength of relational responding within Contextual Behavioral Science research (Hughes et al., 2012). One meta-analysis suggested that the IRAP demonstrates relatively high criterion validity compared to other implicit measures such as the Implicit Association Test (Vahey et al., 2015). However, multiple other meta-analyses have also suggested that the IRAP has poor internal consistency (estimates of from .51 to .60) and unacceptably low test-retest reliability (estimates of *r* from .13 to .43: Greenwald & Lai, 2020; Hussey & Drake, 2020). This presents somewhat of a conundrum, as the reliability places an upper limit on validity (i.e., through attenutation of observable correlations: Revelle, 2009).

One explanation for these seemingly irreconcilable results is that the IRAP literature may suffer from poor replicability, such as inflated effect sizes false positive rates. This is not implausible. Although the IRAP grew out of the behaviorist tradition (Barnes-Holmes et al., 2010), IRAP studies typically employ the same research designs and inference methods as Social and Personality psychology (e.g., Null Hypothesis Significance Testing, NHST), and are therefore subject to the same concerns as any research employing this inference approach. One specific class of statistical methods, multiway Analyses of Variance (ANOVAs), are almost ubiquitous in IRAP research. Research has demonstrated that the modal use of multiway ANOVA inflates false positive rates much higher than the 5% rate implied by the standard alpha level of 0.05 (Cramer et al., 2016). The unavoidable implication is that if the IRAP literature employs a statistical method, which is known to have both inflated false positive rates under modal use and inflated false negative rates under low statistical power, then the published IRAP literature will have inflated rates of false conclusions (i.e., low replicability). At minimum, there is no sound statistical basis by which the IRAP literature could be judged to be a priori immune from such concerns. Rather, the replicability of conclusions in the published IRAP literature must be assessed empirically, via both direct replication studies and assessment of indicators of replicability, such as sample size and statistical power.

It is also worth noting that, given that it is the probability of detecting effects that exist, high statistical power is a desirable property regardless of whether a researcher is employing Null Hypothesis Significance Testing in an inductive manner (Lakens, 2021) or in an inductive manner (e.g., to generate new hypotheses rather than test existing ones). Some IRAP researchers have stated they do the latter (Kavanagh, Matthyssen, et al., 2019), although as an aside it should be recognized that this risks representing a form of Hypothesizing After Results Are Known (HARKing: Kerr, 1998), which lowers the replicability of findings (Munafò et al., 2017). Regardless of a researchers’ self-identified approach as deductive versus inductive, it should be recognized that a smaller number of high-powered studies generally generates a larger number of true conclusions than a larger number of low-powered studies (LeBel et al., 2017).

The current study therefore represents a first effort toward quantifying two related indicators of replicability in the IRAP literature. I performed a systematic review of published research using the IRAP and then applied Fraley et al.’s (2022) approach to estimating median sample size over time and the implied statistical power in this literature.

Sample sizes in the IRAP literature were then contrasted with sample sizes employed elsewhere. Notionally, a comparison with closely related literatures might seem appropriate, such as studies employing other implicit measures such as the Implicit Association Test (Greenwald et al., 1998), Affect Misattribution Procedure (Payne et al., 2005), or Evaluative Priming Task (Fazio et al., 1995). However, this comparison is quite extreme: thanks in part to the popularity of the Project Implicit website ([implicit.harvard.edu](https://implicit.harvard.edu/)), studies employing other implicit measures such as often contain thousands of participants (e.g., Hughes et al., 2022), frequently contain tens of thousands (Bar-Anan & Nosek, 2014; Nosek et al., 2007), sometimes contain hundreds of thousands (Hussey et al., 2019), and occasionally even millions (Xu et al., 2014). Of course, the sample sizes employed in the field of implicit social cognition are apparently large not only in comparison to the IRAP but also in comparison to other areas of Social and Personality psychology. As such, it is perhaps more informative to compare sample sizes in the IRAP literature with a more diverse sample as reference, such as the Social and Personality psychology literature as a whole. I therefore made use of the openly available dataset created by Fraley et al. (2022), which covers the Social and Personality psychology literature.

# Method

Data was obtained from two separate sources. Research designs and sample sizes within the published IRAP literature were obtained via a systematic review. In order to provide a comparison for this literature, existing data on the research designs and sample sizes reported in articles published in nine Social and Personality Psychology journals was taken from a recent openly-available dataset (Fraley et al., 2022). The data extraction method for the IRAP literature based on the example provided by Fraley et al. (2022).

## Systematic review of research designs in the IRAP research (2006-2022)

Results from both searches were integrated. Results of each stage of this review are computationally reproducible: bibtex files for all articles at each stage of the search and exclusion process are available in the supplementary materials ([osf.io/vpwuy](https://osf.io/vpwuy/)) and can be updated by others or used for other evidence synthesis or meta-science purposes.

Both the Web of Science and psycINFO databases were searched. Boolean search terms for the Web of Science database were “implicit relational assessment procedure” OR “IRAP” in the title, abstract, or keywords. Search constraints were publication date between 2006 and 2022, limited to publications in English. The search was run on 23 December 2018. The systematic review was updated with a second search run on 11 September 2022.

**Figure 1.** PRISMA flow chart for systematic review



A PRISMA flow chart detailing all exclusions can be found in Figure 1 (Moher et al., 2009). 372 records were obtained from the database searches and 5 from other sources. After duplicates were removed, 232 records remained. The retained records were screened based on their title and abstract. Inclusion criterion was the use of the Implicit Relational Assessment Procedure (IRAP) within the study. Variant procedures such as the Mixed-Trials IRAP (MT-IRAP: Levin et al., 2010) and the Training IRAP (T-IRAP: Kilroe et al., 2014) were excluded. 161 records remained after title and abstract exclusions. The full texts of these articles was then screened using the same inclusion criterion. Ten articles were excluded based on this full text search. In each case, this was because they did not employ an IRAP (or IRAP variant) at all, or because they employed an IRAP variant such as a Training IRAP or Mixed-Trials IRAP. A list of these exclusions and their individual reasons is available in the supplementary materials. After all exclusions, 151 published articles and book chapters using the IRAP were found that met the inclusion criteria.

The full text for each record was then inspected in order to extract the following information for each study described: the sample size after exclusions (*N*); study design (between, within, or mixed); the number of between-subjects conditions; and whether the study reported employing Null Hypothesis Significance Testing (NHST). The sample size after exclusions was extracted rather than the sample prior to exclusions given the IRAP’s established high attrition rate (Hussey et al., 2015). Note that comparisons among multiple IRAP trial-types was excluded from consideration when labelling a given study as including a within-subjects element, given that this feature is so common in the literature. Where a study employed multiple designs (e.g., both correlating the IRAP with a criterion variable and examining the pattern of IRAP effects between groups) it was labelled “mixed”. As such, “mixed” refers not only to mixed within-between research designs but also articles that report both within and between designs. This was suitable for the current analytic purposes, which required excluding the purely within-subject studies from the analyses in order to estimate statistical power correctly (i.e., using those studies employing at least one between-subjects analysis).

## Review of research practices in Social and Personality Psychology journals (2011-2019)

Fraley et al. (2022) recently reviewed the sample sizes employed in nine Social and Personality Psychology journals (European Journal of Social Psychology, European Journal of Personality, Journal of Experimental Social Psychology, Journal of Personality, Journal of Personality and Social Psychology, Journal of Research in Personality, Personality and Social Psychology Bulletin, Psychological Science, and Social and Personality Psychology Science). The authors extracted data from a random 20% of the empirical studies published in each journal in each year between 2011 and 2019. According to the authors, their chosen start date corresponded to the beginning of the Replication Crisis in psychology, which many would place at the publication of impactful papers by Bem (2011) and Simmons et al. (2011). As in Fraley et al. (2022), (a) only data from studies that employed between-subjects comparisons were employed for the below analyses; and (b) only studies in Social and Personality psychology were included. Studies published in Psychological Science, which is a general psychology journal, were individually screened by Fraley et al. (2022) for their relevance to Social or Personality psychology and excluded appropriately. Their openly available dataset was obtained from their supplementary materials (i.e., [osf.io/rvbxp](https://osf.io/rvbxp/)). The analytic dataset included sample sizes from 3047 studies (range 113 to 631 studies per journal).

# Results

## Analytic strategy

The analyses reported here broadly follow those reported by Fraley et al.’s (2022) quantification of sample size and estimation of statistical power.

In the second section, I assess the distribution of sample sizes in the IRAP literature as a whole, and how median sample sizes have changed over time.

## Prevalence of Null Hypothesis Significance Testing in the IRAP literature

Given that the IRAP emerged from the behavioral tradition (Barnes-Holmes et al., 2010), I considered it possible that some IRAP studies may employ inference methods other than Null Hypothesis Significance Testing (NHST), including Single Case Experimental Design methods. Such studies would be both likely to employ smaller sample sizes and would not be susceptible to issues of statistical power in quite the same way as those which explicitly employed NHST. As such, prior to applying any critique that was relevant only to studies employing NHST, I first began by quantifying the proportion of IRAP publications that actually employed NHST.

One publication did not report the sample size (Cullen & Barnes-Holmes, 2008). The remaining 150 publications contained 188 studies. Just 3 studies in two articles (1.6%) did not employ NHST (i.e., Jackson et al., 2016; Rafacz et al., 2019). The overwhelming majority of published IRAP studies have employed NHST (185 studies, 97.9%). As such, the constraints of inference via NHST necessarily apply to these studies.

## Sample size in the IRAP literature

### Distribution of sample sizes

In the 185 studies that both employed NHST and reported sample sizes, a total of 8384 participants were reported. Sample sizes ranged from 9 to 210 participants, Median = 41, Median Absolute Deviation (MAD) = 17.8. A histogram of the distribution of sample sizes in IRAP research can be found in Figure 1.

**Figure 1.** Histogram of the distribution of sample sizes in IRAP studies.



### Change in sample size per study over time

Change in sample sizes over time was quantified by calculating the median sample size for each year. In order to illustrate the change in sample sizes used in all IRAP studies over time, median sample size per study per year using all studies was calculated (see Figure 2, green line). In this and all subsequent figures, the straight line represents the fitted Ordinary Least Squares linear regression line (discussed later) and the shaded region around it represents its 95% Confidence Interval. As can be seen in the plot, median sample sizes in IRAP studies are small (range 12 to 64). Notably, given that these are medians, this also implies that half of studies in each year employ samples that are even smaller than this. Data from all plots are available in table format in the supplementary materials.

In order to quantify change in an accessible manner, an Ordinary Least Squares linear regression was fit to the data with median sample size as the dependent variable and year as the independent variable. Year was rescored so that 2006 was the intercept. Results demonstrated that estimated median sample size per study was increasing from an estimated 22.5, 95% CI [10.7, 34.2] in 2006 (the model intercept) by an average of 1.8, 95% CI [0.6, 3.1], *p* = .008 participants per year (see Figure 2, green line).

### Change in sample size per group over time

While the previous quantification benefits from including data from all studies and therefore providing an overview of the literature, it does not necessarily compare like with like over time in a way that facilitates understanding statistical power. For example, imagine two studies: the first has a sample size of 100 in two between-subject conditions, the second has a sample size of 100 in three between-subject conditions. The studies have different sample sizes, but this does not translate to them having higher statistical power for their pairwise group comparisons: both have an average of 50 participants per group. In order to compare like with like, it is useful to also plot median sample per group (aka cell within the factorial design). Median sample size per experimental group per year was therefore calculated by dividing the study sample size by the number of between-subjects groups employed within each study. Similarly, in order to compare like with like, only studies employing between groups comparisons were included (69.5% of all studies). This rationale follows that employed by Fraley et al. (2022). Figure 2 therefore also plots median sample size per study per year using all studies was calculated (see Figure 2, blue line).

A similar regression was fitted this time using median sample sizes per group as the dependent variable. Results demonstrated that estimated median sample size per group was increasing from an estimated 10.2, 95% CI [6.8, 13.7] in 2006 (the model intercept) by an average of 0.9, 95% CI [0.5, 1.2], *p* < .001 participants per year (see Figure 2, blue line). Caveats about robustness notwithstanding, because this analysis compares like with like better than the previous one, these result likely represent a better more appropriate estimation of the change in sample sizes over time with regard to implications for statistical power.

**Figure 2.** Median sample size per year in IRAP studies.



## Statistical power in the IRAP literature

I then quantified the median statistical power that these median sample sizes imply. It is important to recall that statistical power is a function of multiple variables other than sample size, and power and sample size should not be treated as synonymous. Power is a function of (1) a specific type of test, (2) its alpha level, (3) whether one-tailed or two-tailed hypotheses are employed, (4) the sample size estimate, and (5) the effect size of interest. Choices must be made for each of these in order to estimate power. As in Fraley et al. (2022), I therefore (1) limited my consideration to specific analyses (i.e., independent *t*-tests or Pearson’s *r* correlations, using equivalent effect sizes for each); (2) employed the standard alpha level of .05; (3) employed modal two-tailed comparisons; (4) estimated the median sample size from the literature that used broadly consistent designs (i.e., median *N* estimated from studies that reported at least one between-subjects comparison, excluding exclusively within-sample designs); and (5) estimated the ability to detect an effect size of Cohen’s *d* = .408. This effect size is equivalent to a Pearson’s *r* = .20 (as used in as used in Fraley et al., 2022), which has been shown in multiple meta-analyses to be approximately the average size effect found across the psychology research literature (Gignac & Szodorai, 2016; Hemphill, 2003; Richard et al., 2003). Other choices of effect sizes are of course possible, but the specific choice of effect size is relatively less important when making relative comparisons (e.g., over time and between literatures). Although estimates of power will differ between different effect sizes of interest, any reasonable choice of effect size allows us to study (a) changes in power over time and (b) differences in average power between research literatures. Implied statistical was calculated using the above parameters for each year using the R package pwr (Champely, 2016). Results can be found in Figure 3. The dotted line represents Cohen’s (1988) commonly accepted guideline for a minimum of at least .80 power. As can be seen in the plot, implied statistical power to detect an average effect size in the IRAP literature is very low (range .10 to .34).

**Figure 3.** The statistical power to detect the average published effect size (Cohen’s *d* = 0.408 or Pearson’s *r* = 0.20) implied by median sample size per group per year in IRAP studies.



In order to illustrate the magnitude of change in power over time, power and median sample size were entered into a regression as the dependent variable, otherwise similar to the previous analyses. Results demonstrated that the implied statistical power to detect the average published effect size (Cohen’s *d* = 0.408, equivalent to Pearson’s *r* = 0.20) was increasing from an estimated .142, 95% CI [.108, .177] in 2006 (the model intercept) by an average of .009, 95% CI [.005, .012], *p* < .001 participants per year. This estimate was used to calculate how long it would take to achieve Cohen’s (1988) recommendation of power of at least .80. If this linear rate of growth continued, the median IRAP sample size would take another 58 years to reach this commonly accepted minimum for statistical power (i.e., in 2080).

## Comparing the IRAP literature with Social and Personality Psychology

The analyses reported in the previous section demonstrate that median sample sizes and implied statistical power in the IRAP literature are low in absolute terms. It is useful to supplement this with a relative comparison, i.e., to research in other areas, using the dataset provided by Fraley et al. (2022). Whereas Fraley et al. (2022) calculated median sample size by journal, I calculate a single overall median for Social and Personality and psychology in order to make a simple comparison between these two literatures.

However, Fraley et al. (2022) did not extract the number of between-subjects groups employed in each study, only the design (between, within, or mixed within-between) and sample size. The most direct and informative comparison possible with the IRAP literature is therefore the comparison of median sample sizes by study in studies that employed between-subjects comparisons (i.e., where the analyses in the previous section compared medians by group rather than by study). Medians and power will therefore differ between the analyses reported in these analyses and those reported in the previous section. Analyses in the previous section represent more appropriate absolute estimates, whereas those reported here are more useful for comparisons.

**Figure 4.** Median sample size per year in IRAP studies compared to Social and Personality Psychology studies.



### Change in sample size per study over time

Figure 4 illustrates the median sample sizes per study per year for IRAP studies (green line) compared to the Social and Psychology literature (blue line). A regression was fitted to the data, with median sample size as the dependent variable; and year, literature (IRAP literature vs. Social and Personality psychology literature), and their interaction as independent variables. The estimate of the interaction effect was used to test the hypothesis that the change in median sample size over time was larger in Social and Personality psychology studies than IRAP studies. Results demonstrated that this difference was statistically significant, substantive in size, and in the predicted direction, *B* = 18.5, 95% CI [14.5, 22.5], *p* < .001.

The statistical power implied by each median sample size was then calculated using the same manner as previously (see Figure 5). Power estimates were then entered into a regression as the dependent variable. The independent variables were identical the previous regression model. The estimate of the interaction effect was used to test the hypothesis that the change in implied statistical power to detect the average published effect size (Cohen’s *d* = 0.408, equivalent to Pearson’s *r* = 0.20) over time was larger in Social and Personality psychology studies than IRAP studies. Results demonstrated that this difference was statistically significant, substantive in size, and in the predicted direction, *B* = .04, 95% CI [.03, .06], *p* < .001.

**Figure 5.** The statistical power to detect the average published effect size (Cohen’s *d* = 0.408 or Pearson’s *r* = 0.20) implied by median sample size per study per year in IRAP studies compared to Social and Personality Psychology studies.



# Discussion

Results demonstrate the sample sizes employed in IRAP literature are problematically small, in both absolute terms and relative to the sample sizes employed in Social and Personality psychology studies. The statistical power to detect the average effect size in published psychology research (i.e., Cohen’s d = 0.408, equivalent to Pearson’s r = .20; REFs) implied by the median sample sizes in IRAP research are also problematically low in both absolute terms (implied power was < .35 in all years) and relative to that in the Social and Personality psychology literature.

Although the sample sizes employed in IRAP studies (and therefore implied power) are increasing detectibly slowly over time, if the current rate of linear increase in median sample sizes continued it would take 58 years reach Cohen’s (1988) recommendation of power of at least .80 (i.e., in 2080).

Results demonstrated that

When compared with the sample sizes employed in 3047 studies published across nine Social and Personality psychology journals (Fraley et al., 2022), results demonstrated that median samples sizes (and therefore implied statistical power) increased at a much greater rate in Social and Personality psychology between 2011 and 2019 than they did in IRAP studies between 2006 and 2022. Furthermore, median sample sizes and their implied statistical power were lower in the IRAP literature in all years than they were at the beginning of the Replication Crisis in Social and Personality psychology in 2011 (and in all subsequent years, see Figures 4 and 5).

## Recommendations for power analyses and sample sizes

Readers might reasonably seek concrete recommendations for sample sizes in future IRAP studies. Unfortunately, my answer may be unsatisfying: (1) it depends, and (2) it should probably be much larger than you think. This position is drawn from a few sources.

First, the authors of the seminal article “False Positive Psychology” paper (2011) have since stated that one of their biggest regrets in that paper was to specify a minimum sample size, due to the subsequent misuse of that recommendation (Simmons et al., 2018). It’s worth noting that similar misuses of sample size recommendations are already visible within the IRAP literature: Vahey and colleagues (2015) reported an analysis of the IRAP’s clinical criterion validity and the results of multiple power analyses based on their effect size estimate. Citations of Vahey et al. (2015) often inappropriately or inaccurately cite these recommendations. For example, many papers make reference to the sample size recommendation reported in Vahey et al.’s (2015) abstract (i.e., “*N* = 29 to 37”) even when the authors are employing a completely different analyses (e.g., other than a one-tailed Pearson’s *r* correlation with -level = .05) and/or are conducting research outside of the clinical domain to which Vahey et al. (2015) limited the scope of their meta-analysis (e.g., Farrell et al., 2015; Kavanagh et al., 2016; Kavanagh, Roelandt, et al., 2019; Leech & Barnes-Holmes, 2020; Maloney & Barnes-Holmes, 2016).

Second, research has demonstrated the researchers’ intuitions about the relationship between statistical power and sample size are inaccurate and tend to greatly over-estimate power (Bakker et al., 2016). Deeper engagement with sample size choices and their power implications is therefore warranted.

In light of the above, it seems important to not provide sample size recommendations that risk being cited or followed unthinkingly, absent of context or specifics. Instead, I encourage readers to think more deeply about their inference method, engage with the concept and calculation of power, and plan their studies accordingly. Researchers should give serious consideration to preregistering their sample size planning justifications, their chosen sample size, stopping rule, analysis plans, and other elements of their research (Nosek et al., 2018). Specifically, sample size involves additional considerations determination beyond power analysis, such as availability of resources and desired precision (Lakens, 2022). Researchers should consider that sample sizes employed in power analyses do not have to be based on as-yet unknown estimates of the effect size they are studying, but can instead be based on the researchers’ Smallest Effect Size of Interest (SESOI: Lakens, Scheel, et al., 2018). Researchers may wish to more deeply consider not only their statistical power (via sample size) but also their chosen -level (Lakens, Adolfi, et al., 2018).

Tests of interaction effects are often reported in the IRAP literature, typically via the interaction term in multiway ANOVAs. Determining statical power for interaction terms is more complex than implied by some power analysis software such as G\*Power (Faul et al., 2007), and I recommend that researchers should base power analyses on specific forms of expected or plausible interactions (e.g., reversed, fully attenuated, partially attenuated) rather than the interaction term in an ANOVA alone (see Sommet et al., 2022). Pin general, power analyses should be conducted and reported in a reproducible manner, for example using the pwr R package (Champely, 2016).

However, authors have also pointed out ways in which these standard power analyses may still under power studies due to between-study heterogeneity. This may require that sample sizes be increased further (McShane & Böckenholt, 2014, who also provide materials for performing power analyses that account for these factors).

## Limitations

It’s possible that the effect sizes observed within the IRAP literature are simply much larger than those observed in other areas of psychology; that the IRAP literature is unique or distinct in some way. This would undermine the comparisons between the implied power in the IRAP literature versus the Social and Personality Psychology literature which are based on an assumption of similar effect sizes. This assumption must therefore be recognized. However, I consider this to be unlikely, given that the IRAP literature (a) considers generally similar phenomena to the broader psychology literature (e.g., correlations between ) and (b) the IRAP has been shown to demonstrate substantially lower reliability of measurement than the measures generally used in social and personality psychology (Greco et al., 2018; Greenwald & Lai, 2020; Hussey & Drake, 2020a). Given that reliability defines and upper limit for correlations among variables (i.e., via attentuation: Revelle, 2009), it is mathematically implausible that a less reliable than average measure should consistently capture larger than average effect sizes.

## Conclusion

Given that statistical power across a literature is a key determinant of the replicability of the findings in that literature, these results paint a worrying picture for the likely replicability of IRAP research. These concerns add to concerns vocalized elsewhere about the IRAP’s reliability (Hussey, 2020; Hussey & Drake, 2020a), a method factor that confounds several common analyses of IRAP data (Hussey & Drake, 2020b), and the fact that most IRAP studies come from a very narrow range of individuals and labs potentially impacting the replicability and generalizability of claims (Hussey, 2022). Researchers should therefore interpret the results and conclusions of published IRAP research with some caution, and be cautious in choosing to employ the IRAP in their own work. In line with a recent statement by the Association for Contextual Behavioral Science explicitly embracing the need for replication studies (Task Force on the Strategies and Tactics of Contextual Behavioral Science Research, 2021), direct assessment of the reproducibility and replicability of IRAP studies is likely warranted.

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# Statements and Declarations

## Conflict of Interest

The author declares that he has no relevant financial or non-financial interests to disclose.

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## Availability of data, code and materials

All data, code and materials are available at [osf.io/vpwuy](https://osf.io/vpwuy/).

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1. For a beginner introduction to statistical power using interactive visualizations, see Magnusson (2023). For a seminal book-length treatment see Cohen (1977). For accessible implementations of power analyses in R see the pwr package (Champely, 2016). [↑](#footnote-ref-1)
2. The median is more suitable than the mean due to strong skew. [↑](#footnote-ref-2)