Abstract

Reporting and interpreting effect sizes (ESs) has been recommended by all major bodies within the field of psychology. In this systematic review, we investigated the reporting of effect sizes in six social-personality psychology journals from 2018, given that this area has been at the center of psychology's replication crisis. Our results highlight that although ES reporting is near perfect (even for follow-up tests), interpreting the magnitude of ESs, including confidence intervals for ESs, and interpreting the precision of the confidence intervals needs development. We also highlight widespread confusion regarding the interpretations of the magnitude of ESs within the context of the research.

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Effect Size Reporting in Social-Personality Research

An effect size can be defined as a quantitative representation of the magnitude of some phenomenon (Kelley & Preacher, 2012). Effect sizes (ESs) allow researchers to move away from identifying evidence for an existing effect (i.e., null hypothesis significance testing, NHST), to quantifying effect size *magnitude* (ESM). As such, there have been recommendations to increase the use and interpretation of ESs (American Education Research Association, 2006; Cribbie, 2017; Cumming, 2014; Flora & Pek, 2017; Wilkinson and the Task Force on Statistical Inference [TFSI], 1999), which have intensified in response to the replication crisis in psychology, especially with respect to social-personality (SP) psychology (Świątkowski & Dompnier, 2017). Building upon previous reviews in psychology, for example, by Sun et al. (2010), this systematic review explored the state of present-day reporting of ESs in SP research, including whether recommendations to include and interpret effects have been followed. Before discussing the review, we provide a brief introduction to the role of ESs and summarize past reviews of effect size reporting in psychology.

Effect Sizes

For decades, NHST has been central to statistical reporting in psychology, with p values and statistical testing results often being the only information provided. This over-reliance on NHST has been convincingly challenged by many (Amrhein et al., 2019; Carver, 1978; Cumming, 2014; Gelman, 2018). NHST focuses on *whether or not* there is evidence that a phenomenon exists. To answer questions about the strength of an association researchers need to estimate and interpret ESs, which allows researchers to pose and answer questions about ESM (Cumming, 2014; Kelley & Preacher, 2012).

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Some have argued for a complete ban on the use of p values (e.g., Trafimow, 2015); however, this practice eliminates valuable information regarding the probability of observing an effect at least as large as that observed (given the null hypothesis). Take a study with a small sample size that observes a large effect; the probability of observing the effect (or one more extreme) under the null hypothesis, given the sample size, may not be small enough to deem the association statistically significant. Similarly, although confidence intervals (CIs) provide valuable information regarding precision, they do not explicitly quantify the probability of observing the effect under the null hypothesis. A more balanced approach has been recommended where ESs are treated as the central outcome of research, and that p values and CIs continue to be reported as supporting, secondary statistical information (Flora, 2020). Despite increased focus on p values, ESs and CIs, we know of no systematic review of effect size reporting in the SP area. SP has arguably been at the center of the replication crisis, where both (a) well known and popular effects within the field have failed to replicate (e.g., social priming), and (b) evidence of rife methodological flaws in SP publications (e.g., Bem and extra-sensory perception; Bem, 2011; Galak et al., 2012; Ritchie et al., 2012) gave way to calls for replication and improved practices within SP (Kahneman, 2012). In fact, the Open Science Collaboration (2015) found that from a replication of 55 social psychology studies, only 14 (~25%) replicated. As such, investigating the frequency and nature of effect size reporting in SP will provide a snapshot of research practice in the sub-field.

Types of Effect Sizes

The majority of ESs can be split into the d and r families. The d or *difference* family of ESs (e.g., Cohen's d , Hedge's g , Glass's delta, raw mean difference) quantifies ESM in terms of the distance between two means. The r family of ESs (e.g., Pearson's correlation coefficient [r],

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semi-partial correlation [sr], partial correlation [r_p], multiple R , multiple R^2 , eta squared [η^2], partial eta squared [η_p^2]), quantifies ESM in terms of the proportion of variability in one variable (e.g., a predictor) that is shared with another variable (e.g., outcome). Note that the unstandardized regression coefficient (B) and standardized regression coefficient (β) do not fall directly within either the d or r families. For convenience, we can classify correlation-based measures and regression coefficients together as strength of relationship measures. Other ESs include odd ratios (OR), relative risk, etc. For a thorough discussion and tutorial regarding ESs, see Ferguson (2016), Fritz et al. (2012), and Volker (2006).

Standardized and unstandardized effect sizes. Both the d and the r families are predominantly comprised of standardized ESs that report mean differences or associations in generic metrics. For example, standardized mean differences quantify ESM in terms of the number of standard deviations separating the means of groups and correlations quantify ESM in terms of the expected change in a variable (in standard deviation units) for a one standard deviation change in another variable. Unstandardized ESs quantify the magnitude of effects in the original units of the variables.

Generally, standardized ESs are used to compare ESM across studies and variables because they are unit-less (e.g., comparing the correlation between depression and anxiety in two different samples, or when using different measures of these constructs), though there are psychometric issues associated with this practice (Pek & Flora, 2017). Unstandardized ESs are typically easier to interpret within the context of a given study because they are a direct reflection of the units used within the study. However, they are more difficult to interpret when using variables with unknown scales or when trying to compare ESs across divergent measures. It is recommended to explicitly interpret ESM within the context of the research (Anderson,

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2019; Beribisky et al., 2019; Cumming, 2012; Ferguson, 2009; Flora, 2020; Kelley & Preacher, 2012; Ozer, 2019; Pek & Flora, 2017; Wilkinson & The APA Task Force on Statistical Inference, 1999; Zakzanis, 2000; Ziliak & McCloskey, 2004).

Confidence Intervals for Effect Sizes. Recall that an X% CI is a range of values over which the true population parameter will be captured in X% of the intervals from successive samples (Neyman, 1937). CIs for ESs are no different, and allow us to gauge the precision with which a study has captured an effect. The interpretation of the width of a CI for an effect depends on the scaling of the measure and the context of the study (e.g., substantive or clinical implications). When the lower and upper bounds of a CI are relatively close to the point estimate, this suggests that the true effect size may not be markedly different from the point estimate. All else considered equal, larger samples lead to narrower and more precise confidence regions around a given point estimate of an effect. For examples of CIs for ESs, see Lee (2016).

Issues in the Reporting of Effect Sizes

Reporting Any Effect Size. The first issue concerns the reporting of any effect size. Prior reviews have found that effect size reporting in different disciplines has varied anywhere from 1% to 87% (Sun et al., 2010). With a push for better reporting practices as a way to combat the replication crisis (Asendorpf et al., 2013), it would be useful to review whether these recommendations have been adopted. Despite evidence of being quite heavily impacted by issues of reproducibility (Świątkowski & Dompnier, 2017), the effect size reporting of SP researchers has not been extensively examined.

Interpreting Effect Sizes. Past reviews across multiple disciplines have found that ESs and their accompanying CIs are often not interpreted (Alhija & Levy, 2009; Fritz et al., 2012; Karadaghy et al., 2017; Sun et al., 2010), but guidelines suggest that a study's findings are

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clearest when they are interpreted within the substantive research context (e.g., Beribisky et al., 2019). Although the basic reporting of ESM is beneficial to researchers conducting systematic reviews/meta-analyses, it is vital that researchers comment on the magnitude of the effect given their unique expertise, including the context of the study (variables, theories, participants, past research, etc.). Moreover, ESs should be reported and interpreted regardless of the test statistic's statistical significance. Further, effect size interpretations may be avoided in complex statistical designs due to more nuanced variance components in complex designs (Fern & Monroe, 1996), though readers arguably benefit the most from such an interpretation.

Effect Size Labels and Context. Importantly, interpreting standardized effects with reference to labels such as small, medium, and large (Cohen, 1988) is generally not recommended as judgements of practical significance depend heavily upon the context in which the effects are embedded (Beribisky et al., 2019; Cohen, 1988; Hemphill, 2003; Pek & Flora, 2017). Cohen (1988) clarified that small effects are real but can only be identified through methodical study. On the other hand, large ESs are consistent and obvious enough to be noticed without empirical investigation (e.g., the relationship between height and weight). In some contexts, small ESs may have large practical consequences, especially if their benefits outweigh their costs. For example, many educational or medical interventions that improve academic performance or decrease medical symptoms are associated with small ESMs, but are of substantial benefit when generalized to entire populations (Coe, 2002). Other examples include the well-cited study that aspirin reduces the risk of heart attack, with a small effect size of $r = .03$ ($r^2 = .0009$; Rosnow & Rosenthal, 1989; Steering Committee of the Physicians' Health Study Research Group, 1988), or the link between lead exposure and IQ (Reuben et al., 2017).

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Likewise, unstandardized ESs that are commonly included in software output (e.g., regression coefficients) need to be interpreted with respect to variable scaling (Pek & Flora, 2017).

Omnibus Tests. Ideally, if an omnibus test (e.g., ANOVA or a linear model) implies a follow-up test, these tests should also be reported and interpreted with appropriate ESs. For example, if a one-way ANOVA is conducted and pairwise comparisons are used to clarify the nature of the mean differences, ESs should be reported for each pairwise comparison. The effect size for the omnibus test tells us very little about the effect of interest (i.e., the pairwise mean differences). In general, it is most important to provide ESs for the lowest order test conducted (Cribbie, 2017).

The Present Study

The present systematic review seeks to explore effect size reporting within SP. By reviewing several high-impact SP journals from 2018, we investigated (1) what proportion of articles provide and interpret an effect size for their main hypothesis and follow-up tests, (2) what proportion of articles report and interpret confidence intervals around ESs for their main hypothesis and follow-up tests, (3) whether the complexity of the statistical model used is related to the reporting and interpretation of corresponding ESs, (4) the frequency with which standardized and unstandardized ESs are reported, and (5) whether researchers discuss the relationship between NHST and effect size results.

Method

Data Sources

Focusing on journals with the highest impact factors according to the Journal Citations Report for the year 2017, journals were excluded if they were primarily review journals (e.g.,

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Personality and Social Psychology Review), if they were not primarily empirical, and, given that some of our hypotheses relate to null hypothesis testing (e.g., relationship of statistical significance to magnitude of effect size), if they did not report p values (e.g., *Basic and Applied Social Psychology*). Six journals were selected among a short list of SP journals with the highest impact factors, all with a 2017 impact factor > 2.5 : *Social Psychological and Personality Science* (SPPS), *European Journal of Personality* (EJP), *Journal of Experimental Social Psychology* (JESP), *Journal of Personality and Social Psychology* (JPSP), *Journal of Research in Personality* (JRPL), and *Personality and Social Psychology Bulletin* (PSPB). All articles published in these journals in the year 2018 were reviewed, except for those exclusively reporting qualitative research, simulation studies, scale validation, reviews, editorials, or journal announcements.

Review and Coding Procedures

A 40-item checklist was adapted from Sun et al. (2010) (see the Appendix). The first 4 items pertained to descriptive information regarding the article and sample, the next 21 items pertained to effect size reporting and interpretation for the primary hypothesis of the study, and the remaining 15 items pertained to the reporting of follow-up analyses, when appropriate (e.g., simple effects, pairwise comparisons).

The “type of analysis” referred to the specific statistical model utilized (item 5). We then categorized the analysis based on level of complexity: t test, correlation, linear regression, ANOVA, and chi-square goodness of fit or test of independence were classified as simple/moderate, while generalized linear models, structural equation modelling (SEM), hierarchical linear modeling (HLM), network analysis, the actor-partner interdependence model, multidimensional scaling analysis, and discriminant analysis were classified as complex. We

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acknowledge that the classification of the different methods into these categories is somewhat arbitrary; however, this research question is valuable and thus we deem the practice justifiable. The reporting practices of each article were coded into several categorical outcomes: a) ES reported versus not (item 6), b) the ES family: *d*, *strength of relationship*, OR, or other (items 9 and 10), c) whether the reported effect size was unstandardized or standardized (items 11/12; note that simply reporting a table of means for study variables was not sufficient to be classified as reporting an unstandardized effect size, the authors had to discuss or report mean differences as well; furthermore, when the symbol β was used we verified that the authors were referring to the standardized coefficient), d) ES interpreted with respect to ESM within the context of the research vs. not (item 15), e) discrepancy between ES and NHST decision (i.e., was an effect size reported if the primary hypothesis was not supported; item 23), and f) relationship between NHST decision and ESM explicitly discussed versus not (item 24; e.g., “although variable X was a statistically significant predictor of Y, X explained very little of the variability in Y”).

The process of establishing a high level of interrater agreement involved multiple stages. The first stage involved training in the nature and types of ESs available to researchers. Second, all authors met to derive a preliminary checklist of items for recording the use and interpretation of ESs by researchers. Third, all authors individually coded five randomly selected articles and reviewed discrepancies in coding, items to add/drop, etc. After finalizing the checklist, authors again coded the five articles to check for any remaining issues. Finally, the three primary coders each coded 10 articles and the percentage agreement across subjective items was calculated. Across all 10 (articles) x 36 (subjective items coded for each article) = 360 items, there was agreement across all reviewers for 351 (97.5%) of the items. The primary item which led to inconsistencies between raters was the final sample size used for analysis, which can be difficult

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to ascertain due to dropouts, imputation, etc. (but is not a primary outcome variable for the study).

Analysis

We examined the simple frequencies pertaining to our coded items, and in many cases this information represented our primary outcome (i.e., the unstandardized effect size, or for proportions, the standardized effect size). Where a test statistic was required, we conducted a series of logistic regressions and reported accompanying odds ratios to represent ESs. We constructed a model with complexity of analysis as a binary predictor (simple/moderate vs. complex) and whether or not an effect size, or an interpretation of the effect size, was reported as separate binary outcomes, in order to examine whether analysis complexity was associated with effect size reporting practices. We also assessed whether primary hypothesis support vs. non-support (i.e., statistically significant vs. non-significant test statistic) predicted effect size reporting. Next, we tested whether incompatible conclusions between the effect size and the p value (present or absent) predicted any discussion of the relationship between effect size and p value (present or absent). All statistical tests were conducted at a two-tailed $\alpha = .05$.

Results

Descriptive Information

In total, we coded 518 empirical articles published in 2018. The median sample size of the studies was $N = 204$. The number of articles meeting inclusion criteria within our six SP journals was as follows: $n = 99$ from *Social Psychology and Personality Science*, $n = 142$ from *the Journal of Experimental Social Psychology*, $n = 110$ from *Personality and Social Psychology Bulletin*, $n = 95$ from *the Journal of Personality and Social Psychology*, $n = 52$ from *the Journal of Research in Personality*, and $n = 20$ from *the European Journal of Personality*. Sixty-three

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percent of primary analyses conducted were classified as simple to moderate, whereas only 37% of primary analyses were considered complex.

Reporting of Effect Sizes

Out of 518 articles, 97% ($n = 503$) reported an effect size for the primary research question (Table 1). Of the 134 studies that conducted a follow up test, 87% ($n = 116$) reported an effect size associated with the follow up test. However, it was deemed that some form of a follow up test was appropriate for 309 (60%) primary analyses, but over half of these articles ($n = 178$) did not conduct any follow up analysis. Table 1 summarizes our findings.

Nature of Effect Sizes Reported

Seventy-eight percent of all reported ESs for primary hypotheses ($N = 544$) were standardized measures (β : $n = 115$, η_p^2 : $n = 104$, r : $n = 71$, Cohen's d : $n = 69$, η^2 : $n = 38$, OR: $n = 13$, r_p : $n = 11$). However, the most prevalent effect size was the unstandardized regression coefficient (B : $n = 123$). Of note, no authors used an unstandardized mean difference as a primary effect size. The distributions of the more common effects were positively/right skewed, especially for standardized regression coefficients (β) and η_p^2 (Figure 1). The magnitude of the absolute values of the ESs are as follows: β : $Med = .18$, range = 0 – 1.34, IQR = 0.21; η_p^2 : $Med = .09$, range = 0 - .81 IQR = 0.1525; r : $Med = .35$, range = .02 - .97, IQR = 0.27; Cohen's d : $n = 69$, $Med = .56$, range = 0.06, 1.96, IQR = 0.44. Only one article discussed the relationship between the NHST results (statistically significant or not), and the effect size results (i.e., magnitude of the effect). We did not run a chi square test of independence

Table 1. Summary of study outcomes ($N = 518$ articles)		
Reporting/Interpretations of effect sizes		
	Primary hypothesis	Follow-up
Any ES	97% ($n = 503$)	87% ($n = 116$)
Interpreted the reported ES in context	60% ($n = 300$)	9.5% ($n = 11$)
Interpreted the reported ES using a cutoff	7% ($n = 38$)	3% ($n = 3$)

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Model complexity	63% simple/moderate; 37% complex	NA
Follow up test (when appropriate)	26% ($n = 134$)	NA
Effect size for follow up test	87% ($n = 116$)	NA
Confidence intervals		
CI for effect size	54% ($n = 294$)	39% ($n = 45$)
Interpretation of CI	2% ($n = 5$)	0% ($n = 0$)
Frequency of ES metrics		
Standardized measures	78% ($n = 544$)	78% ($n = 90$)
Measure of mean differences Cohen's d	13.6% ($n = 69$)	32.8% $n = 38$
Measure of strength of relations β B r r_p η_p^2 η^2	83.8% ($n = 424$) $n = 115$ $n = 123$ $n = 71$ $n = 11$ $n = 104$ $n = 38$	62.1% ($n = 72$) $n = 15$ $n = 23$ $n = 5$ $n = 0$ $n = 22$ $n = 7$
Others OR	2.6% $n = 13$	0.9% $n = 1$
Discussion of discrepancy between NHST result and magnitude of effect	$n = 1$	NA
Model complexity		
Differences in reporting between different statistical models/levels of complexity	Among simple to moderate analyses, 99% ($n = 320$) reported an effect size, whereas among complex analyses, 94% ($n = 177$) reported an effect size.	
Odds of reporting an unstandardized effect size	1.8 times greater for complex analyses Among complex analyses, unstandardized effects comprised 30% of all reported effects, whereas unstandardized effects comprised 19% of simple to moderate analyses.	

to examine whether statistical significance was related to reporting of any effect size because almost all articles included at least one effect size for their primary hypothesis. Similarly, for follow up tests, 78% of all reported ESs ($N = 90$) were standardized measures (β : $n = 15$, η_p^2 : $n = 22$, r : $n = 5$, Cohen's d : $n = 38$, η^2 : $n = 7$, OR: $n = 1$). The most prevalent unstandardized effect size was once again the unstandardized regression coefficient (B : $n = 23$).

Interpretations of Effect Sizes

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Ninety-three percent ($n = 506$) of all ESs were not accompanied by a small, medium, or large label according to Cohen's established cut-offs. Further, 40% of effects ($n = 218$) were not accompanied by a specific interpretation of the magnitude of the effect within the context of the research variables. As stated above, only one article discussed the relationship between p values and ESM, so we did not formally test whether incompatible conclusions between the effect size and the p value (present or absent) predicted any discussion of the relationship between effect size and p value (present or absent). For follow up tests, 97% ($n = 113$) of all ESs were not accompanied by a Cohen established cut-off, and 89% ($n = 103$) were not paired with an in-context interpretation.

Figure 1. Distributions of effects sizes for commonly reported metrics.

Confidence Intervals

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Just over half (54%, $n = 294$) of all reported ESs were not accompanied by a CI around the point estimate, and of those that did include a CI, only 2% ($n = 5$ articles) interpreted the precision/width of the CI (e.g., “given the narrow CI around our point estimate, our effect size has been measured relatively precisely”). However, examining the CIs separately for proportion of variability and mean difference measures, it was much less common for a CI to accompany an η^2 measure (28% of η^2 measures included a CI vs. 49% of Cohen’s d measures that included a CI). For follow up tests, CIs around point estimates were reported for 39% ($n = 45$) of the ESs. No articles that included a CI interpreted its precision for the follow up tests. Similarly, for follow up tests, 29% of η^2 measures included a CI vs. 30% of Cohen’s d measures.

Model Complexity and Reporting Practices

A logistic regression predicting reporting practices from model complexity revealed that those conducting simple or moderate-level analyses were about 11 times (OR = 0.09, 95% CI: 0.01, 0.34, $p = .002$; $1/\text{OR} = .09$) more likely to report an effect size ($\chi^2(1) = 12.59$, $p < .001$, though this was accompanied by a small effect size, Cramer’s $V = .17$; Table 2), but recall that 97% of authors reported an effect size associated with their primary hypothesis, so this test may be a bit misleading due to ceiling effects. However, those conducting a simple/moderate analysis were about as likely as those conducting a complex analysis (OR = 1.19, 95% CI: 0.81, 1.76, $p = .12$; $1/\text{OR} = 0.84$) to interpret their ESs within the context of their research. Among simple/moderate level analyses, 7% ($n = 22$) interpreted ES based on Cohen’s guidelines, whereas among complex analyses, 8% ($n = 15$) interpreted ES based on Cohen’s guidelines.

Table 2. Logistic regression predicting effect size reporting from analysis complexity

Outcome:	Log Odds	Odds Ratio, 95% CI	1/Odds Ratio
Any ES	-2.38 ($p = .002$)	0.09 (0.01, 0.34)	11.11

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ES interpretation	0.20 ($p = .56$)	1.22 (0.61, 2.41)	0.82
Std. Vs unstd.	0.59 ($p = .007$)	1.80 (1.17, 2.76)	0.55

Note. 'No' = 0, 'Yes' = 1 for the outcome, except for Standardized effects = 0 and unstandardized effects = 1 for the last outcome. Analysis complexity as predictor was coded simple/moderate = 0, complex = 1.

Finally, the odds of reporting an unstandardized effect size was about 1.8 times greater for complex analyses (OR = 1.80, 95% CI: 1.17, 2.76, $p = .007$). Among complex analyses, unstandardized effects comprised 30% of all reported effects, whereas unstandardized effects comprised 19% of simple to moderate analyses. Lastly, analysis complexity did not predict reporting of confidence intervals (OR = 1.13 [95% CI: 0.78, 1.62]) interpretations of CIs (OR = 1.03, [95% CI: 0.13, 6.31]), interpretation of effects within context (OR = 1.62 [95% CI: 0.89, 2.97]), or interpretations of effects using Cohen effect size cut-offs (OR = 1.22 [95% CI: 0.61, 2.41]). To compare, Sun et al. (2010) found no difference in effect size reporting across complex models (60%), moderate-complexity models (49%) and simple models (47%), Cramer's $V = .06$.

We found a small association between reporting practices and level of model complexity. Among simple to moderate analyses, 99% ($n = 320$) reported an effect size, whereas among complex analyses, 94% ($n = 177$) reported an effect size, thus our comparison is not meaningful because almost all studies reported an effect size. Detailed comparison between studies is provided in Table 3.

Discussion

The field of psychology has placed greater value on transparency and methodological improvements in recent years. Decades of overreliance on p values/NHST have been countered with recommendations to shift towards the reporting and interpretation of ESs (and associated confidence intervals), regardless of the test's statistical significance. ESs should be the focal

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statistic in research reporting as they reflect strength of associations and allow inferences to be drawn about implications of research findings in the real world. SP has been a focus of the replication crisis primarily due to its prior proclivity for underpowered studies and between-studies designs, which has been shifting in recent years to higher powered studies and within-subject designs (Schimmack, 2020). Therefore, it would also be reasonable to assume that the most change in effect size reporting practices have occurred in this field. This led us to systematically review these practices within the field of SP for 2018, focusing on the frequency and nature of reporting practices. For a review of the replication crisis and its responses within SP, see Schimmack (2020).

Table 3. Comparisons in outcomes to Sun, Pan, and Wang (2010)		
	Sun, Pan, & Wang (2010)	Current results
Percentage of articles with any ES	49% ($n = 610$)	97% ($n = 503$)
Percentage that interpreted the reported ES	57% ($n = 346$)	60% ($n = 300$)
Model complexity	16.4% simple; 75.5% general linear models; 8.1% complex models	63% simple/moderate; 37% complex
Differences in reporting between different statistical models/levels of complexity	complex models: 60%; general linear models: 49%, and simple tests: 47%	Among simple to moderate analyses, 99% ($n = 320$) reported an effect size, whereas among complex analyses, 94% ($n = 177$) reported an effect size.
Frequency of different types of ESs		
Measure of mean difference ^a	26% ($n = 156$)	13.6% ($n = 69$)
Measure of strength of relations ^b	62% ($n = 383$)	83.8% ($n = 424$)
Others ^c	12% ($n = 71$)	2.6% ($n = 13$)

^a Cohen's d ; ^b β , η_p^2 , r , r_p , B ; ^cOR

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Some of our outcomes can be directly compared to results reported in the review by Sun et al. (2010) on effect size reporting practices in education and psychology. They coded 1243 articles published in 14 journals between 2005 and 2007. While Sun et al. (2010) reported that 49% of articles reported some form of effect size, our results show almost all articles reported some effect size for the primary hypothesis (97%; see Table 2). This indicates a substantial improvement in the quantity of effect size reporting over the past decade. However, of those that reported an effect size, the percentage that interpreted the reported effect size was similar between the reviews (57% in Sun et al. (2010) vs. 60% in the current review). This suggests little improvement over the past decade in interpretation.

Sun et al. (2010) reported a small relationship between model complexity and effect size reporting, however, comparisons with our data would not be meaningful since almost all studies reported an effect size. The most frequently interpreted effect size measures in both the Sun et al. (2010) review and our review were measures of strength of relations (62% and 83.8%, respectively). In the Sun et al. (2010) review, there were differences in the interpretation of ESs based on level of model complexity, Cramer's $V = .11$. Articles with complex models were more likely to interpret effect size than others. We found no differences in interpretation of ESs between level of complexity.

Another important area of reporting that was generally neglected in SP journals was the interpretation of the ESMs in context. Although arbitrary cut-offs were rarely used (which is generally thought of as a positive outcome), interpretations of specific magnitude can be improved, as 40% of articles did not include an interpretation of effects related to the specific substantive phenomena. However, this coding item led to differences between coders and journals. This may be due to journals having different policies that result in very drastic

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differences in the frequency of in-context interpretations. For example, according to the journal websites, EJP recommends that authors include ESs, CIs, and carefully consider whether the data and results support inferences drawn and whether ESs are discussed within the context of the research. According to the JESP website, authors are advised to report ESs, but not CIs or interpretations of ESMs. The journal websites for PSPB and SPPS require reporting of ESs and CIs for all primary research findings.

Another reason is that what constitutes an “in-context interpretation” differs between coders. Take the following statement: “Given the relationship between length of therapy and therapy outcome in depressed senior citizens, both in this study and past studies, it is important for therapists working with this population to continue therapy for at least 8 weeks.” The interpretation mentions context (variables, population, psychological issue), however, simply stating “the relationship” does not address the magnitude of the effect. In another example, Lee et al. (2018) presented the following interpretation: “the personality factor scale showing the strongest association with political orientation was Honesty-Humility (- .21), followed by Openness to Experience (- .17); that is, lower Honesty-Humility and lower Openness were each modestly associated with a more right-wing political orientation. These results are consistent with recent studies showing the central role of these two factors in the domains of ideology and values (e.g. Lee et al., 2010).” Again, there is mention of study context (variables, past studies, practical consequences) and magnitude, but there is no explicit link to the magnitude of the effect within context (i.e., quantifying practical significance). As Kelley and Preacher (2012) note, “translating the effect size along with the corresponding interval estimate into meaningful substantive terms is something that we see as a principal use of ESs. Some studies report ESs but interpret the results from only the perspective of a dichotomous reject or fail-to reject outcome

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from a null hypothesis testing framework, perhaps with only an additional consideration of the direction of the effect size.” This implies that more than simply a yes/no or directional interpretation of an effect size is needed. The main issue is that there are few recommendations or good examples of how such interpretation should be framed. The nuanced and subjective nature of judging whether an effect size has been interpreted ‘in-context’ creates a challenge for coders to reliably classify interpretations into a single category. Future research may explore more qualitative classification of effect size interpretation, rather than the yes/no classification we chose.

One recommendation is to consider the stage of research when framing an effect size interpretation. Pek and Flora (2017) have argued that the direction of the effect is the priority in early stage research, while later stage research characterized by consensus in measures and replications should shift focus to the magnitude of effects and practical implications. Future research may examine how early stage vs. later stage ESMs are interpreted.

Furthermore, readers benefit most from the interpretation of effects produced in complex models. However, this appears to be where improved effect size reporting and interpretation is most needed. Reporting and interpreting of ESs was less likely in complex models. Unstandardized effects, which necessitate in-context interpretations, appeared more often in complex models than standardized ESs. Unfortunately, likely due to increased model complexity, ESM is least likely to be interpreted for more complicated models.

One limitation of the research is that only ten articles were coded by the primary reviewers for establishing interrater reliability. Despite high agreement across 360 subjective items (97.5%), this sample of articles may not have been representative of the various analyses and ESs reported in our broader pool of articles. Another limitation is that articles published in

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other SP journals would not be reflected in the sample of studies. However, our focus on higher impact journals was deliberate as these journals tend to set the standard for model complexity and effect size reporting.

In conclusion, almost all researchers report some form of effect size for primary hypotheses, however, they rarely accompany those effects with CIs and a discussion of the precision of the estimated ESs. Although context dependent interpretations of ESs are not always straightforward, they should always be reported with consideration not on generic cut-offs or the distribution of ESs in the discipline (Panzarella et al., submitted), but instead the magnitude of the ES within the context of the study. They may be reported either in unstandardized or standardized units. CIs should accompany ESs, though at this point the frequency of their reporting can be improved and interpretations of CIs are very rare. It is more useful to report ESs for specific rather than global tests, such as omnibus ANOVAs. Finally, researchers almost never link their NHST results to their effect size results. It is important to note, however, that researchers, journals, and editors are adapting to the current zeitgeist of the *new statistics* (Calin-Jageman & Cumming, 2019). Such adaptation takes time and effort to master. The good news is that there is evidence of gradual progress as suggested by this study's results indicating substantial quantitative improvements in the reporting of ESs. We hope that substantive improvements in ES reporting and interpretation will follow in the near future.

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Declarations

Competing interests: On behalf of all authors, the corresponding author states that there is no conflict of interest.

Ethical statement: N/A (no Research Ethics Board was consulted as human participants were not directly included in this study).

Consent to participate: N/A (no human participants directly studied in this study).

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