Questionable Research Practices in Single-Case Experimental Designs: Examples and Possible Solutions

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Please Cite as Follows

Tincani, M., and Travers, J. C. (in press). Questionable Research Practices in Single-Case Experimental Designs: Examples and Possible Solutions. In W. O'Donohue, A. Masuda, & S. O. Lilienfeld (Eds.). *Questionable research practices: Designing, conducting, and reporting sound research in clinical psychology*. Cham, Switzerland: Springer Publications.

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Abstract

Questionable research practices (QRPs) are a variety of research choices that introduce bias into the body of scientific literature. Researchers have documented widespread presence of QRPs across disciplines and promoted practices aimed at preventing them. More recently, Single-Case Experimental Design (SCED) researchers have explored how QRPs could manifest in SCED research. In the chapter, we describe QRPs in participant selection, independent variable selection, procedural fidelity documentation, graphical depictions of behavior, and effect size measures and statistics. We also discuss QRPs in relation to the file drawer effect, publication bias, and meta-analyses of SCED research. We provide recommendations for researchers and the research community to promote practices for preventing QRPs in SCED.

Key words: single-case experimental design, questionable research practices, publication bias, open science

Questionable Research Practices in Single-Case Experimental Designs: Examples and Possible Solutions

Single-case experimental designs (SCED) are used by social and behavioral sciences researchers to evaluate effects of clinical interventions on therapeutic outcomes. Rooted in B.F. Skinner's (1953) radical behaviorism, these designs began to appear widely in journals in the 1960s – 1980s (Barlow & Herson, 1984), and remain popular today. SCED are found in a broad array of clinical fields and specialties (e.g., Krasny-Pacini & Evans, 2018; Lobo et al., 2017; Tanious & Onghena, 2019). Whereas group designs rely on inferential statistics to determine average experimental effect between groups, SCED employ visual analysis of individual responding between conditions, with each subject serving as their own control. SCED require fewer subjects to demonstrate experimental control, typically 3- 5, as statistical power requirements for group design samples are not applicable.

SCED employ inductive reasoning to determine functional relationships between independent and dependent variables. Often, following a period of baseline data (A condition), in which an individual's responding is measured repeatedly in the absence of the intervention, an intervention (B condition) is applied, and repeated measurement continues. If application of the intervention corresponds with therapeutic changes in level, trend, and variability of targeted responses, the researcher concludes with some degree of confidence the intervention was effective (i.e., there was a functional relationship between the intervention and observed outcomes). The researcher's confidence in a functional relationship increases with replications of experimental effect. SCED researchers employ a variety of designs that permit both within and between subject replication (Ledford & Gast, 2018). Two SCED are most common. In the reversal design, following baseline (A), an intervention (B) is applied, removed, and then

reapplied. The multiple baseline (MB) design entails multiple A-B series where baseline condition lengths are staggered and intervention is introduced at different points in time (across different behaviors, participants, and settings). There are numerous variations in SCED that include combined designs like, for example, the MB design with a reversal. Figures 1 and 2 show hypothetical examples of reversal and multiple baseline designs demonstrating experimental effect as evidenced through visual inspection.

< FIGURE 1 HERE >

< FIGURE 2 HERE >

As inductive research designs, a noteworthy feature of SCED is flexibility for adaptation according to each subject's response to an intervention. For example, if a subject's improvement with an intervention (B^1) is insufficient to meet desired clinical thresholds, a therapeutic modification to the intervention (B^2), or a new intervention (C), can be introduced, and any improvements can be evaluated accordingly (e.g., Crozier & Tincani, 2005). Such inductive design adaptations mitigate risk of clinical treatment failure associated with more traditional group designs, and permit a closer examination of factors that appear to influence treatment responsiveness.

As with other research design traditions, contemporary SCED researchers have established consensus on what constitutes rigorous study features in line with key design elements (Horner et al., 2005; Kratochwill et al., 2010; Ledford et al., 2018). These include selection of target behaviors and interventions that align with consumer preferences and values (i.e., social validity; Schwartz & Baer, 1991); precise operationalization of outcome variables with measures to establish reliability; complete and replicable descriptions of treatments with

documented fidelity; sufficient data points within conditions to establish functional relations (or non-responsiveness); and design features that permit replication of experimental effect.

Outcomes of studies reflecting these collective elements are considered more trustworthy than those that do not.

Questionable Research Practices

Questionable research practices (QRPs) are a variety of research choices that introduce bias into the body of research literature. The most blatant QRPs include undisclosed researcher conflicts of interest; post-hoc selection of statistical techniques to support a priori hypotheses (p-hacking; Head et al., 2015); post-hoc creation of hypotheses in accordance with observed results (harking; Kerr, 1998); selectively reporting data in published articles (Piggot et al., 2013); and outright suppression of results (Rosenthal, 1979). However, more subtle forms of QRPs are also likely quite common (Gerrits et al., 2019). Writing an article abstract to downplay non-significant findings, interpreting findings in the results to overplay significant findings, or changing the order of findings in the discussion from the aims of the study are examples of these more subtle QRPs. In the context of our current discussion, we conceive QRPs in the broadest sense to include both researcher and editorial behavior. For instance, a manuscript author might selectively report data in a paper submitted for publication to make results appear more favorable, or an editor might request an author to omit data in a revision of a paper, or otherwise reject a paper, because it contains unfavorable results.

Scientific researchers in a variety of fields have documented widespread presence of QRPs and have promoted practices aimed at preventing them. One of the most prominent efforts is the open science movement, which includes calls for pre-registering studies and making all study data publicly available (Nosek et al., 2015). Open science practices prevent more blatant

QRPs when researchers declare publicly their study hypotheses, data collection procedures, and data analysis techniques in a transparent manner prior to conducting a study. Similarly, publicly sharing of datasets prevents omission of data in research reports and enables outside researchers to replicate and conduct their own independent analyses of the data. Other measures aimed at preventing QRPs include editorial practices that promote publication of studies with non-significant results, and calls for publication of registered reports, a type of peer-review whereby research papers are accepted for publication with the introduction and methods only (Scheel, Schijen, & Lakens, 2021). The latter practice ensures authors follow methods and analysis procedures they committed to prior to conducting the study and prevents journal editors and reviewers from biased editorial decisions based on study results.

QRPs in SCED

While QRPs have been documented in a variety of research fields, examination of QRPs has until recently tended to focus exclusively on mainstream group design approaches. Only recently have SCED researchers focused any significant attention on whether QRPs are present with these designs, and if so, what should be done about it (Tincani & Travers, 2018; 2019). Clearly, there is potential overlap between many QRPs in the broader researcher community and QRPs as they could manifest in SCED. Given both SCED and group design studies involve formulation of research questions and collection of data, biases related to selective reporting of results or post hoc alterations of research questions could occur regardless of design. Nonetheless, unique features of SCED suggest certain QRPs are likely to appear differently within these designs, and other QRPs not present in group designs might appear uniquely in SCED. What follows is a description of several key QRPs that could manifest in SCED, and steps SCED researchers and the SCED research community can take to mitigate them. Where

useful, we include hypothetical examples of QRPs in SCED. We acknowledge examination of QRPs in SCED is a relatively new area of study and this is not necessarily an exhaustive list of practices. We hope our tentative discussion and recommendations will inspire future research aimed at examining these important concerns.

Participant Selection

Because SCED studies typically employ a small number of participants who serve as their own controls, often fewer than five in a given study, participant selection bias is a potential concern. This QRP occurs when experimenters selectively recruit participants whose behavior is more likely to change therapeutically with application of an intervention (i.e., selection bias; Gast & Ledford, 2018). Of course, this is a potential problem with any study of a therapeutic procedure, but the threat is mitigated to a degree in group designs, as outcomes of an intervention are aggregated across a larger number of participants within a treatment group, and one or more comparison groups are not exposed to the intervention.

It is typical with any SCED study for a therapeutic intervention to target a population with a common set of characteristics. For example, interventions that improve functional communication skills should target participants who would most likely benefit from the intervention due to clinical diagnoses associated with poor functional communication, such as severe autism spectrum disorder (ASD; Ganz, 2015). Selecting study participants from a population most likely to benefit from successful intervention is an important aspect of social validity and definitely not a QRP. However, intentionally selecting a subset of participants within a population because the experimenter knows, or at least suspects they will perform better than the target population at large, is a QRP.

The following example illustrates participant selection bias. A hypothetical research team is interested in evaluating an intervention to teach basic communication skills using speech generating devices (SGDs) to children with severe ASD (Tincani et al., 2020). The specific intervention involves teaching children to select picture icons from a computer screen which activates corresponding voice output. As part of their participant recruitment procedures, the team interviews parents about their children's current communicative skills, and while none of the children is currently using an SGD, they learn that one child has a history using a different albeit similar type of picture-based communication system. The team encourages the parents to consent for participation because they suspect this child will more easily acquire communication once the intervention is introduced, enhancing the appearance of experimental control (i.e., treatment effect). Consequently, it is impossible to tell how much of the observed results are due to the intervention effects or due to the participant's reported history of exposure prior to the study.

Participant selection bias in SCED can be prevented in the following ways. First, the description of recruitment procedures for a study should clearly detail all criteria for participation, along with a thorough description of recruitment procedures, to make clear participants were not selectively recruited based on potential intervention responsiveness. Considering the previous example, this would include screening questions that exclude participants for previous exposure to the intervention or highly similar interventions, or other characteristics that could selectively enhance intervention responsiveness. Second, researchers could employ a randomization procedure to recruit participants. This would begin with the researchers identifying a pool of participants whose characteristics match those of the study, and then randomly selecting a subset of individuals for participation. A limitation of the latter

approach is the researcher must have a sufficient participant pool for randomization, which may not always be the case, especially if the target population has a rare or low incidence condition and few potential participants are readily available.

Independent Variable Selection

This QRP is a type of data falsification that occurs when researchers intentionally select or modify independent variables to enhance the appearance of intervention responsiveness, or to support their a priori hypotheses (Tjebk, Verbeke, & Smulders, 2014). This includes simplifying operational definitions of target behaviors on one or more salient dimensions, effectively lowering the bar for a successful outcome. This also includes omitting key response dimensions from operational definitions to enhance the appearance of success.

Consider a hypothetical research team evaluating an intervention to teach vocational skills to adults with intellectual and developmental disabilities in a community work setting. After observing participants in their work setting, they select a work task consisting of 15 steps completed in sequential order; the task is considered learned when participants complete all 15 steps with 100% accuracy. During the baseline condition, researchers note that while participants complete most steps with poor and inconsistent accuracy, steps 1 and 2 are especially challenging and are almost never performed correctly. Anticipating these steps will be especially difficult to teach with intervention, the team omits them from the task analysis, so participants must complete only 13 steps with 100% accuracy. Participant data during baseline and intervention are graphed as a percentage of steps completed correctly; therefore, omission of the two steps is not reflected in the data. A different problematic example would be if researchers selected a different and easier to perform target behavior altogether, and then began from scratch collecting new baseline data on the easier-to-perform behavior.

The potential for target behavior selection bias can be mitigated as follows. First, researchers should provide evidence that operational definitions of target behaviors reflect all key dimensions of meaningful dependent variables. In the previous example, this would include evidence that participants' work supervisors (or other secondary consumers, as appropriate) were consulted on target behavior selection prior to the baseline condition, and they verified all relevant steps of the target behavior were included in the task analysis, which remained consistent during baseline and intervention. Pre-registration of the study prior to initiation, including complete operational definitions of each target behavior, enhance research transparency and prevent researchers from modifying target behaviors in ways that work against an unbiased approach. Finally, avoidance of graphing dependent responses using less dimensional measurement systems (e.g., percentage correct) in favor more dimensional measurement systems (e.g., frequency correct) lessens the likelihood that data is depicted in a deceptive way (Johnston, Pennypacker, & Green, 2010).

Procedural Fidelity Documentation

Thus far, our discussion of QRPs has focused on ways researchers can manipulate dependent variables to produce the appearance of favorable findings. Data collection on independent variables can also be manipulated in ways that enhance appearance of a study's credibility. Procedural fidelity, the degree to which experimenters adhere to a specified experimental protocol, is a key part of SCED intervention research (Ledford & Wolery, 2013). Documenting strong procedural fidelity is critical for demonstrating that changes in the dependent variable are attributable to changes in the independent variable. Conversely, poor or inconsistent procedural fidelity reduces the researcher's confidence that observed outcomes are attributable to treatment.

In SCED, procedural fidelity is typically documented using a checklist of steps that represent adherence to the treatment protocol, often completed by a researcher implementing the procedure along with secondary observers to ensure reliability. If a treatment is particularly complex, the checklist may have many steps, including ones that are conditional based on participants' response to an intervention; a study may have multiple checklists representing different phases of intervention. The percent or number of treatment steps completed is often reported as a measure of procedural fidelity in SCED research reports. In reports published in refereed journals, the percent or number of completed steps reported typically is high. However, low fidelity to the treatment protocol usually is considered a threat to internal validity and reduces chances of the study's publication (Tincani & Travers, 2018).

Maintaining high procedural fidelity can be challenging, particularly if a treatment protocol is complex. In lieu of rigorous training to ensure close adherence to a stated protocol, researchers may simplify a protocol checklist to omit key steps of an intervention, or use generalized descriptions of procedural steps to increase the likelihood of yes responses on a checklist. For example, rather than describing the checklist steps consistent with the stated procedure, "The therapist delivers verbal praise immediately after a correct response or corrective feedback immediately after an incorrect response", the checklist simply states, "The therapist delivers feedback." The latter description would more readily engender a "yes" response regardless of whether the feedback was correctly given. In a different and more blatant example, if a treatment step requires particularly skillful implementation that is prone to error, researchers could simply omit the step when calculating fidelity and bolster the apparent adherence to the protocol and chances of publication.

To prevent QRPs in procedural fidelity documentation, researchers should make their procedural fidelity checklists or similar forms publicly available. This level of transparency allows readers to compare the stated experimental procedure with the method of procedural fidelity documentation and the reported procedural fidelity data. Sharing details of procedural fidelity documentation can be accomplished through inclusion in a published manuscript, in a publicly available data repository associated with the journal's publisher, or other public data repository like the open science framework (<https://osf.io>). Also, where possible, researchers should employ secondary, blinded observers who do not implement the treatment to complete procedural fidelity checklists.

Graphical Depictions of Behavior

SCED studies involve graphical depiction of data for visual analysis to determine experimental control. QRPs can manifest when researchers depict behavior on graphs to enhance the appearance of experimental effect. Specifically, researchers can modify dimensions of the Y-axis scale of a graph to enhance the appearance of a robust treatment effect where less treatment effect actually exists (Dart & Radley, 2017). Consider the three hypothetical graphs depicted in Figure 3. Each graph depicts the same results, but the scale of the Y-axis scale varies between 10, 20, and 40. As the largest unit on the Y-axis increases, the appearance of treatment effect is lessened, since the vertical distance between the data paths and the floor of the graph decreases, and the vertical distance between the data paths in the two phases also decreases. Researchers may intentionally select a lower maximum Y-axis scale value, like the one shown in the bottom panel of Figure 2, to enhance the appearance of treatment effect.

< FIGURE 3 HERE >

Some SCED researchers have recommended use of standard graphical displays, which would prevent misrepresentation of SCED data by varying the Y-axis scale (Calkin, 2005). Currently, such standard displays are not in wide usage. Alternatively, two rules of thumb in scaling the Y-axis should be followed. First, where multiple graphs representing the same dependent variable are presented (e.g., across different participants or settings), the Y-axis scaling should be consistent across the graphs. Second, the maximum value of the Y-axis should correspond with the optimal level of *socially significant behavior change*, rather than simply defaulting to the highest level of behavior observed during the experiment. For example, in a study of a reading intervention where the goal is to teach students to read 120 words-per-minute, the maximum Y-axis value should be *at least* 120 regardless of whether participants' maximum reading performance fell below 120 words-per-minute. In this way, readers can interpret results of the experiment in relation to the established goals of intervention.

Effect Size Measures and Statistics

SCED researchers rely primarily on visual analysis to determine whether changes in trend, level, and variability of behavior indicate experimental control for interventions. In addition to visual analysis, researchers have devised a variety of effect size (ES) measures and statistical tests to estimate treatment effect in SCED research (Parker et al., 2011; Parker & Brossart, 2003; Shadish et al., 2014). These techniques are specific to SCED since the assumptions of statistical tests used with group design research are often violated or not applicable to SCED datasets. The most commonly used procedures evaluate non-overlap of data between baseline and intervention conditions. Additionally, a wide variety of parametric and non-parametric statistical techniques have been developed to quantify magnitude of treatment effect between baseline and intervention conditions. While these techniques have become

increasingly commonplace in meta-analyses of SCED studies, they also frequently appear in single SCED study reports (Bondy & Tincani, 2018).

Use of statistics to quantify behavior change has long been an area of controversy and disagreement in the SCED research community, with some arguing these methods cannot adequately capture dynamic aspects of visual analysis and should be staunchly avoided (e.g., Baer, 1977). Others contend these methods are useful in addressing shortcomings of visual analysis (e.g., lack of precision, need for training), including when synthesizing a body of literature to determine whether an intervention is effective (Kratochwill & Levin, 2014). There is evidence to suggest inconsistent and, in some cases, poor correspondence when quantitative measures are compared to each other, and when quantitative measures are compared to visual analysis (Wolery et al., 2010; Yucesoy-Ozkan et al., 2020; Zimmerman et al., 2018). Furthermore, each available quantitative technique has salient limitations. For example, non-overlap methods provide no quantification of the magnitude of experimental effect, and statistical approaches may be compromised by certain properties of SCED data, such as autocorrelation and trend within conditions (Dowdy et al., in press-a). Although these techniques are continually evolving and show promise for quantifying SCED data in more robust ways, currently there is no single statistical analysis technique that captures all aspects of visual analysis.

Incorporation of ES measures and statistics in SCED research is not itself a QRP. However, statistical methods of analysis create the possibility of QRPs. In the absence of robust treatment effect as evidenced by visual analysis, researchers may be tempted to include a quantitative measure to bolster the appearance of treatment effect. This seems especially likely when researchers can find one or more measures that will yield a moderate to large ES estimate.

This QRP is similar to p-hacking in the group design research literature. Given myriad quantitative metrics available, different assumptions and calculation procedures, and varying results, this QRP is a very real possibility. To prevent this, researchers should publicly report and provide a rationale for specific ES metrics and statistical tests (along with visual analytic techniques) before the experiment. Importantly, given limitations of current quantitative techniques for SCED data, we strongly recommend researchers use these techniques for individual study datasets only after well-established visual analysis approaches have been used (Lane & Gast, 2014; Harrington, & Velicer, 2015; Kratochwill & Levin, 2014). Finally, given the novelty of some techniques and lack of wide usage across the SCED literature, we recommend researchers provide an explanation for why and how a particular technique will be used, how the data assumptions for the technique are met with the current dataset, and any anticipated limitations with the technique.

The File Drawer Effect and Publication Bias

The file drawer effect is a longstanding problem in the social and behavioral sciences research literature (Rosenthal, 1979). It occurs when studies that fail to yield statistically significant results are not published in refereed journals. If the study is part of a policy report, doctoral dissertation, or master's thesis, it will forever remain as part of the grey literature, unless it is incorporated into a published research synthesis that includes grey literature (e.g., Dowdy et al., 2020). Non-significant findings are crucial in understanding how interventions can fail to achieve desired therapeutic effects (e.g., Lang et al., 2012). The file drawer effect is problematic as it results in a skewed research literature disproportionately represented by successful outcomes (Scheel et al., 2021; Gage, et al., 2017).

The file drawer effect is thought to be a manifestation of publication bias (Tincani & Travers, 2019). Publication bias occurs when researchers selectively submit studies showing positive effects for publication, and/or when journal reviewers and editors favor such studies when rendering editorial recommendations and decisions. Publication bias also occurs when researchers selectively report study data showing positive effects to increase the likelihood of publication. As with other QRPs, publication bias can manifest with either group design or SCED research. For example, researchers using any type of design who have invested substantial time and resources to develop an intervention might be disinclined to publish data showing equivocal or negative effects of the intervention. Similarly, journal reviewers and editors may consider non-significant or negative results uninteresting or otherwise indicative of a poor study. One unique aspect of SCED research is the longstanding view that strong experimental control is the hallmark of a good study (Tincani & Travers, 2018). That is, a study is worthy of dissemination only when researchers demonstrate control over behavior through application of an intervention. Shadish et al. (2016) found that SCED researchers were more likely to rate a dataset as publishable if it demonstrated strong experimental control. In contrast, since contemporary SCED are used to evaluate a wide variety behavioral, educational, psychosocial, and other therapeutic interventions, it is crucial that failures to produce therapeutic effects are documented in published research (Johnson & Cook, 2019). This information is critical in facilitating consumers' knowledge of the boundaries of interventions, including those in widespread usage (Leaf et al., 2021).

Journal editors can implement editorial practices that foster publication of non-effect studies. Stated editorial policies should explicitly encourage authors to submit for publication studies that fail to yield experimental control (Kittelman et al., 2018). Journal editors can provide

instructions to reviewers as guidance on how to review these studies, outlining features of high quality SCED that fail to produce optimal therapeutic effects (Tincani & Travers, 2018). Registered reports also may increase publication of non-effect studies (Johnson & Cook, 2019). In registered reports, researchers submit the introduction (i.e., rationale) and method for conducting a study for publication prior to conducting the experiment. Assuming a solid rationale and adherence to registered experimental procedures, journals are obligated to publish the final manuscript (with results and discussion) regardless of the direction of findings. The acceptance for publication based on the proposed study and strict adherence to the accepted method precludes the possibility of editorial decisions biased by study findings. Scheel et al. (2021) found that registered reports included substantially more studies demonstrating non-statistically significant findings, compared to papers published through the typical peer review process. Registered reports show promise for disseminating non-effect findings of both group design and SCED studies, yet they are not currently in wide usage in journals publishing either types of design (c.f., Cook, Maggin, & Robertson, 2021).

Research funding agencies can counter publication bias by encouraging researchers to incorporate open science principles into their research. This includes requiring research grant recipients to preregister their studies on open science platforms (e.g., U.S. Department of Education, 2020). Granting agencies should also encourage researchers to incorporate open science principles into their grant applications, and advise reviewers to score them accordingly. For instance, granting agencies can allow applicants to achieve maximum review scores only if they commit to submitting at least a portion of their research for publication as registered reports, and otherwise demonstrate they will take explicit steps to disseminate non-effect studies, along with other open science practices.

Meta-Analyses of SCED Research

Thus far we have restricted our discussion to QRPs to individual SCED studies, but QRPs can occur with syntheses and meta-analyses. Increasingly, SCED researchers have adapted meta-analysis techniques to aggregate findings across individual studies to specify what interventions work, for whom they are effective, and under what conditions effects are observed (Dowdy et al. in press-a; Maggin et al., 2011). Meta-analysis is an established research methodology in the social and behavioral sciences, and SCED researchers have been adopting these techniques in their work for decades (Allison & Gorman, 1993; Shadish et al., 2008; Vannest et al., 2018). However, many SCED researchers are unfamiliar with contemporary meta-analysis techniques as they apply to SCED, and lack training in requisite statistical techniques used in meta-analysis (Dowdy et al., in press-a). Given these concerns, QRPs can manifest when researchers employ less-than-rigorous procedures to conduct meta-analyses of individual SCED studies (Jamshidi et al., 2018).

As with any research methodology, there are established standards for conducting high quality meta-analyses to which all researchers should adhere (e.g., Moher et al., 2009; Shea et al., 2007). These include a priori formulation of research questions, rigorous procedures for extracting targeted studies, strategies for detecting bias within studies, and procedures for evaluating quality of studies. Many of these standards are the same regardless of whether researchers are synthesizing group design studies, SCED studies, or both together (e.g., Gage et al., 2017). However, there are at least two unique considerations for SCED meta-analyses. First, as discussed, ES estimation and statistical procedures for aggregating SCED data are different than those for aggregating group design data, with little consensus among SCED researchers for which is best given a particular dataset. Therefore, as with individual SCED studies, we strongly

recommend SCED researchers preregister their meta-analysis studies on an open science platform, such as PROSPERO (Booth et al., 2012). They should provide a rationale for and associated assumptions for their selected ES metric. Researchers also should describe how the assumptions are likely to be met by the proposed dataset and explain the calculation procedures. Additionally, we strongly recommend researchers report multiple ES metrics and explain any differences between results obtained from the different metrics. In addition, researchers may wish to consider reporting structured visual analysis techniques in tandem with ES metrics (Lane & Gast, 2014).

Second, given the possibility of publication bias, we strongly encourage SCED researchers to include grey literature in their meta-analyses. We recommended that any meta-analysis include procedures for detecting publication bias, such as the funnel plot technique (Duval & Tweedie, 2000). However, given differing statistical assumptions of SCED experiments, procedures for detecting publication bias in group design studies may not be appropriate for SCED studies (Dowdy et al. in press-b). Alternatively, to detect publication bias, SCED researchers can calculate ES metrics for published studies and grey studies separately and compare them (Dowdy et al., 2020; Sham & Smith, 2014).

Conclusion

We discussed several QRPs in SCED research and outlined tentative solutions for preventing them. In drawing attention to QRPs in SCED, it is not our intention to convey that SCED research is less rigorous or somehow more prone to these practices (though we do recognize that many researchers are unfamiliar with and have incorrect understandings of SCED research). In fact, some well-documented QRPs like p-hacking are less likely to occur in SCED given the traditional reliance on visual analysis over statistics to determine experimental effect.

Nonetheless, QRPs can manifest in any research methodology or scientific discipline, and SCED researchers are not immune from them. Clearly, more research on questionable practices in SCED is needed to better understand the scope of these misguided research choices, and how they appear uniquely within SCED. For example, surveys of researchers in other fields have revealed that QRPs are commonplace (Gerrits et al., 2019; Loewenstein & Prelec, 2012; Tjldink et al., 2014). We hope our tentative discussion in this chapter sheds light on the possibility of QRPs in our research, and encourages researchers, journal editors, and other members of the research community to embrace practices to prevent them.

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Figure 1

Reversal Design Graph with Hypothetical Data

Figure 2

Multiple Baseline Graph with Hypothetical Data

Figure 3

Variations in Y-Axis Scaling to Alter Appearance of Experimental Effect