# Chapter 10 – Approaches to formal sample size determination

## Abstract

Researchers routinely have to decide upon the sample size they include in their research. When formal sample size planning is used it is important to understand that the approach to sample size selection (e.g., AIPE or power analysis) as well as the method used to develop the alternative hypothesis (i.e., the effect sizes and parameter estimates used in power analysis) has important implications for the appropriate interpretation of the results. This paper presents the results of analysis of the sample size planning approach used in 121 empirical research articles published in the November 2017 to August 2018 issues of Psychological Science, and uses the results of this analysis to illustrate a guide to sample size planning under the most common methods of sample size determination (power analysis, Accuracy in Parameter Estimation, Statistical Assurance, and Bayesian sample size determination). This paper provides guidance on how to select effect sizes under these different approaches, and explains the implications that follow from each selection method while reinforcing some important warnings against practices that are likely to lead to inaccurate or sub-optimal estimates of the power of planned research.

## Introduction

Researchers routinely have to decide upon the sample size they include in their research. If they decide to use formal sample size planning tools like power analysis to do so, they must specify the effect size and other parameters that are required for power analysis. There are two main approaches to effect size selection that are commonly discussed in the psychology literature, estimating power at the expected effect size (Anderson, Kelley, & Maxwell, 2017), or estimating power at a minimum interesting or clinically significant effect size (Biau, Kernéis, & Porcher, 2008). A third approach that is less commonly employed is to use a Bayesian prior distribution over effect sizes and parameters, either to estimate ‘assurance’, the probability that a study will find significant or sufficiently precise estimates in a frequentist framework (Ren & Oakley, 2014), or to estimate the probability of developing convincing evidence or precise credible interval estimates if a Bayesian approach to statistical analysis is to be used.

Any formal sample size determination method posits a hypothetical scenario (or probability distribution over effect sizes) and is only meaningful with regards to the proposed parameter values or prior distribution. Estimating the effect, minimum effect of interest, or using a Bayesian prior distribution may be appropriate in different circumstances, although they provide different information. This paper outlines these different approaches to selecting effect sizes in formal power analysis and clearly explains the implications of each, as well as reinforcing some important warnings against practices that are likely to lead to inaccurate or sub-optimal estimates of the power of planned research.

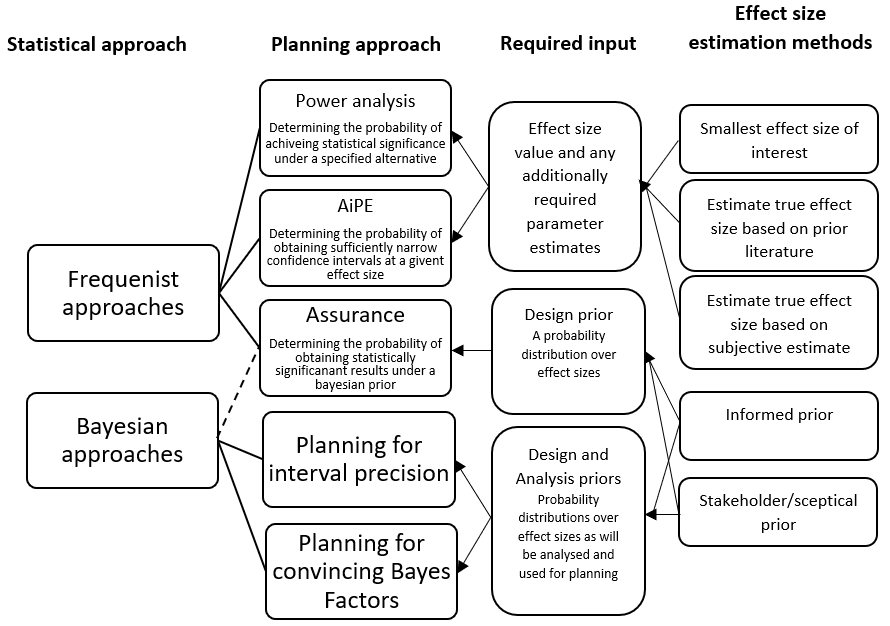


Figure [approaches to formal sample size planning]. Figure showing the different approaches to effect size estimation determination in different statistical frameworks.

## Terms

Box [Definitions]

**Statistical power**

The probability of obtaining statistically significant results from a given statistical analysis under a specific alternative hypothesis.

**Power analysis**

The process of estimating the statistical power of a particular analysis given a set of specified population parameters and test characteristics (e.g., a sample size, effect size, alpha level, and the number of groups included)

**Accuracy in Parameter Estimation (AiPE)**

The process of estimating the probability of obtaining sufficiently precise confidence intervals under a set of specified population parameters and test characteristics (e.g., a sample size, effect size, confidence level, and the number of groups included)

**Assurance**

The probability that a frequentist statistical procedure will achieve a given goal (e.g., statistical significance or sufficiently precise confidence intervals) given a set of specified test and design characteristics (e.g., sample size, alpha level, the number of groups included in the analysis) and a Bayesian design prior over the effect size of interest.

**Sample size planning for Bayesian interval precision**

Estimating the sample size necessary to obtain a specified probability of obtaining sufficiently precise Bayesian credible intervals given a specified Bayesian Design and Analysis prior.

**Sample size planning for convincing Bayes Factors**

Estimating the sample size required to obtain a specific probability of obtaining sufficiently convincing Bayes Factors using a particular Bayesian analysis given a specified Bayesian Design and Analysis prior.

**Bayesian Design Prior**

A specified distribution over effect sizes to be used in the planning of studies (often a distribution of expected effect sizes)

**Bayesian Analysis Prior**

A specified distribution over effect sizes to be used in the planning of studies (often representing a sceptical observer or one of a number of default priors)

**Confidence level**

The confidence level of a confidence interval describes the probability that a particular statistical procedure will contain the true population parameter given that the statistical procedure’s assumptions are met.

## Approaches to formal sample size planning

In frequentist sample size determination, such as power analysis or Accuracy in Parameter Estimation (AiPE), researchers must specify an alternative hypothesis and research design in sufficient detail to determine the sampling distribution of the test statistic under a specific alternative hypothesis. This allows for an examination of the expected behaviour of a particular statistical analysis under the specified alternative hypothesis. For relatively simple designs (e.g., for a comparison of the mean scores of two independent groups or correlational analysis) the specification of a single standardised effect size (e.g., a Cohen’s *d* or Pearson’s *r*) and sample size characterises the sampling distribution under the alternative hypothesis adequately for power analysis (Cohen, 1988). For more complex designs (e.g., when covariates are to be included or when repeated measures designs are used) additional parameters may need to be specified such as the correlation between repeated measures and the number of included variables.

Whatever approach to statistical analysis is taken, when formal sample size planning is used it is important to understand that the method used to develop the alternative hypothesis (i.e., the effect sizes and parameter estimates used in power analysis) impacts the meaning of the results. Under no approach is it possible to discover the ‘true’ statistical power of a proposed analysis, the true effect size is never known (Morey & Mayo, 2017, July 26th), and these different approaches to estimating effect sizes lead to very different interpretations of the estimated statistical power of an analysis.

**What approaches are currently being used?**

In order to get an initial estimate of the research planning practices common in psychology I assessed the 121 empirical research articles published in the November 2017 to August 2018 issues of Psychological Science. Of the 121 empirical research articles published during this period 51 articles reported a power analysis, 42% of sampled articles (95% Wilson score interval [34%, 51%]). None reported using any other technique (e.g., AIPE to plan for precise interval estimates or Bayesian sample size planning methods). Of the reported power analyses, the most common approach was to effect size selection was to use a single previous study as the effect size, with 12 articles (10% of examined articles) reporting having done so. Despite the fact that pilot studies are (almost by definition) too small to reliably estimate the true population parameter value of interest, 3 studies (2% of articles) reported having estimated the effect size with this value. Almost as many used benchmarks from Cohen (1988; n = 9, 7% of articles). Six articles (5%) reported a sensitivity analysis, showing the effect size that the sample size gave them 80% power to detect. Seven articles (6%), did not provide any justification for the effect size they reported having used in power analysis, and 4 articles (3%) did not state the effect size that they used in a reported power analysis. Just 3 articles, 2% of those examined, reported that they adjusted their estimates for publication bias, and all of these articles used ad-hoc methods such as doubling the sample size that resulted from a power analysis or using the lowest reported effect for an intervention as opposed to the more sophisticated methods that have been proposed (e.g., Anderson et al., 2017; Perugini, Gallucci, & Costantini, 2014). See <https://osf.io/bmv2d/> for the data behind the above description and table [Psych sci] for the number and percentage of papers reporting each type of justification for the effect sizes reported in their power analysis along with multinomial confidence intervals on the percentages of papers in each group.

Table [1]. *The number and percentage of papers reporting each type of justification for the effect sizes reported in their power analysis along with multinomial confidence intervals on the percentages of papers in each group.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  | 95% CI | |
| Effect size selection method | n | Percentage | LB | UB |
| No power analysis reported | 70 | 58 | 50 | 67 |
| Single previous study | 12 | 10 | 2 | 19 |
| Informal assertion of effect size | 7 | 6 | 0 | 15 |
| Medium effect benchmark from Cohen | 6 | 5 | 0 | 14 |
| Sensitivity analysis | 6 | 5 | 0 | 14 |
| No effect size stated | 4 | 3 | 0 | 12 |
| Average effect size in a set of studies (not a formal meta-analysis) | 3 | 2 | 0 | 11 |
| Effect size from a pilot study | 3 | 2 | 0 | 11 |
| Small effect benchmark from Cohen | 3 | 2 | 0 | 11 |
| Average effect size in a set of studies (not a formal meta-analysis), reduced for publication bias | 2 | 2 | 0 | 11 |
| Effect size from meta-analysis | 2 | 2 | 0 | 11 |
| Lowest effect size reported in a previous paper on this topic | 1 | 1 | 0 | 10 |
| Rule of thumb supported by power analysis | 1 | 1 | 0 | 10 |
| Smallest effect size from set of pilots | 1 | 1 | 0 | 10 |

Because of the infrequency with which the accuracy in parameter estimation (AIPE) approach (sample size planning to constrain confidence interval width) is reported (e.g., never in this relatively small sample of research), we focus on power analysis in the current paper. However, when researchers are hoping to precisely estimate effects as opposed to investigating their presence or absence, AIPE techniques provide a more appropriate method of planning sample sizes than power analysis (Maxwell, Kelley, & Rausch, 2008). Although the following discussion of effect size selection methods focuses on their implications for statistical power, but the concepts apply equally to sample size planning for interval width.

### Approach 1: estimating the population effect size

The most common approach to effect size selection for formal sample size planning in psychology is to develop an estimate of the effect size under study, an approach often presented as the only way of performing formal sample size planning (e.g., Kadam & Bhalerao, 2010; Kim & Seo, 2013). In this approach the researcher proposes a hypothetical scenario and says that if the true effect size was equal to their estimate (and all other statistical assumptions are met), the study would reach statistical significance on a given percentage of experiments (a value commonly and arbitrarily set at 80%). Often the estimated effect size is justified using a previous effect size from the literature or a meta-analytic effect size estimate. Failing that, the researcher uses their intuition to estimate the effect size. In so far as articles explicitly identified having used any of the available approaches to selecting effect sizes for power analysis in the examined issues of Psychological Science, almost all of the articles reporting a power analysis at least implicitly suggested that this was the goal of their power analysis (i.e., those using effect sizes from a single precious study, meta-analysis, average effects seen in previous research, effect sizes from a pilot study and informal assertions of the effect size).

While this approach is the most common, it may be the most error prone as minor differences in the choice of effect sizes will lead to large differences in the sample sizes that result (Wagenmakers et al., 2015). This is the only method of sample size determination that involves estimating the true effect size of the planned study, and the ‘required’ sample size is only as reliable as the effect size estimate that is used. If a researcher chooses arbitrarily, or adjusts their effect size estimate in order to achieve a certain level of apparent power at an achievable sample size, formal sample size planning is of little use. Any sample size greater than one has 80% power to detect a large enough effect size, while simultaneously being severely ‘underpowered’ to detect a sufficiently small effect size.

The main difficulties in this approach are, firstly, identifying a sufficiently similar body of similar research which from which adequately reliable estimates can be developed, and secondly accounting for simple random variability and the likely impact of publication bias on the observed magnitude of effects.

#### Selecting a similar body of research

Selecting a sufficiently similar sample will often be an inherently subjective decision. Given that as little as 1% of published psychology research psychology are direct replications of previous experiments (Makel, Plucker, & Hegarty, 2012), in the great majority of research psychologists have to base the effect size estimates on bodies of research that are markedly different in at least some aspects. The situation is simpler in the case of direct or partial replications, where a previous study may provide a direct estimate of the effect under study, although even in this case it will often be appropriate to adjust for publication bias. A researcher must use their expert judgement to identify a set of previous studies which are sufficiently similar to act as reasonable estimates of the type of effect that could be reasonably expected from the type of research that is being performed. Once this body of research, parameters required for power analysis must be extracted. In the case of simple research designs, this is usually possible from just the test statistics and reported effect sizes. Even when previous studies have not reported effect sizes directly many effect sizes (such as *d*, partial eta squared and *r*) that are required in popular power analysis computer programs (Faul, Erdfelder, Lang, & Buchner, 2007) are readily calculable from reported sample statistics and their associated degrees of freedom, or from reported means and standard deviations. See chapter [effect size measures] for definitions and plain language descriptions of the most commonly used effect sizes for power analysis, and that chapters’ supplementary materials for a description of how they can be extracted from more commonly reported test statistics and effect sizes.

#### Accounting for effect size imprecision and exaggeration

If using this approach, once a sufficiently similar body of research has been identified, it is important to account the imprecision of previous effect size estimates and publication bias (Anderson & Maxwell, 2017). In the assessed Psychological Science articles, 12% reported directly using a power analysis based on a single effect size estimate from a previous study. Even ignoring publication bias, imprecision in the parameter estimates chosen can be problematic. Using effect sizes directly from the previous literature will lead to power estimates inflating the apparent power at least 50% of the time simply on the basis of sampling variability (Taylor & Muller, 1996). Because power is a concave function of sample size, directly using point estimate from previous studies to power experiments will lead to the mean level of power being below the desired level (McShane, Böckenholt, & Hansen, 2016). You get more severely punished for underestimating the effect size than you get rewarded for overestimating the effect size.

***-Insert plot of difference from ideal power over power estimation difficulty here-***

Publication bias compounds this issue, as the point estimates of effect sizes seen in the psychological literature are likely to be overestimates of true effects (Anderson et al., 2017) [effect size adjustment paper]. A recent examination of the effect sizes seen in direct replications suggests that, on average, the effect sizes seen in direct replications are decreased as much as 20%, 95% credible interval [11%, 28%] even when we condition on the true effect size being non-zero, and also shows that there is considerable heterogeneity across replications [effect size adjustment paper]. It is difficult to accurately account for publication bias in meta-analysis, and it is likely that many of the effects sizes reported in meta-analysis are also upwardly biased (Ferguson & Brannick, 2012; Hartwig, Davey Smith, Schmidt, & Bowden, 2018; Thompson et al., 2011).

However, methods have been developed to account for sample variability inherent point estimates of effects sizes or parameters (see Anderson et al., 2017; McShane & Böckenholt, 2016; Perugini et al., 2014; and Taylor & Muller, 1996). These methods are all designed to estimate the sample size required to adequately power a direct (or exact) replication study. The simplest method of adjusting effect sizes, suggested in Camerer et al. (2018), is halving effect size estimates from the published literature to arrive at a reasonable estimate of the true effect size. Perugini et al. (2014) propose safeguard power, using the lower bound of a 100-x% confidence interval as opposed to the point estimate in order to have 100-(x/2)% confidence (in the statistical sense), that the study will have adequate power to detect the true population parameter. However, the actual confidence level achieved is only indicative of the true level of confidence a researcher could have in the absence of any type of selective reporting, an unlikely assumption in practice. Even when all assumptions hold this method will tend to overestimate the required sample size on average (Perugini et al., 2014).

A third approach has been proposed McShane and Böckenholt (2016), the Power Calibrated Effect Size approach (PCES). PCES produces an effect size estimate that accounts for the variability in the point estimate such that the expected power of a study using this effect size will be powered at a chosen level of power. PCES is equivalent to the assurance approach (detailed below), using a prior distribution over the parameter of interest assumed to be normally distributed with a mean set at the point estimate from a previous study and a standard deviation set to the standard error of the test statistic. McShane and Böckenholt (2016) provide easily implemented formulas for tests of differences between independent and dependent means and proportions as well as correlation coefficients. They also provided a website at which these methods can be used at <https://blakemcshane.shinyapps.io/pces/>.

A final method developed by Taylor and Muller (1996) and discussed in depth in Anderson et al. (2017) has been developed to account for publication bias. This method does not use the maximum-likelihood estimate of the effect size assuming an uncensored test statistic distribution (e.g., an F distribution), but instead to uses a maximum-likelihood estimate of the effect size assuming a truncated test statistic distribution (they suggest that it should be truncated at the critical value, i.e., at the test statistic which leads to statistical significance). The lower bound of an 100-x% confidence interval around the effect size this can be used as the effect size measure in order to achieve 100-(x/2)% confidence (i.e., the expected long run frequency of studies which will be adequately powered) assuming that F-statistics are only reported given that they reach statistical significance. Anderson and Maxwell (2017) provide an easy to use website that makes the implementation of their method much less complex that it may sound (www.DesigningExperiments.com).

These methods for adjusting for publication bias are rarely used. This means that that some the most common methods of effect size selection (using effects from previous studies, either individual studies or from collections of studies) are likely to be optimistic estimates of power of the proposed research. Only three articles examined from Psychological Science reported attempting to account for publication bias. All three used ad hoc methods, one doubling the sample size they recruited from that returned by a power analysis using effect sizes from the literature, one reducing effect sizes by an arbitrarily chosen amount and one using the lowest effect size reported in a set of studies on their effect of interest. In fact, it seems entirely possible that these more complex methods of effect size adjustment may have never been used to plan research. A literature review performed by Anderson and Maxwell (2017) of articles citing Taylor and Muller (1996) and Perugini, Gallucci, and Constantini (2014) showed that none of the examined articles had actually used either of these methods to plan their sample sizes.

These methods of adjusting effect also rely on researchers being able to identify a sufficiently similar piece of research. It may not be uncommon for a researcher performing novel research to not feel capable of identifying a sufficiently similar set of studies for a power analysis to be meaningfully performed if the power analysis relies on a plausibly accurate effect size estimate to be generated. Although it is not uncommon for people to suggest that power analyses could be based on pilot studies (e.g., Kim & Seo, 2013), in so far as most pilot studies are not large enough to develop sufficiently precise estimate effect sizes for inferences about even the presence or absence of effects, using a point estimate from a pilot is likely to be of very little use (Albers & Lakens, 2018). However, it may be possible to use conservative estimates from aspects of the pilot study to inform aspects of sample size planning (e.g., using the value within a 95% CI around a standard deviation that leads to the largest required sample size) (Lancaster, Dodd, & Williamson, 2004). This same approach, taking the most conservative estimate from a pilot study’s 95% confidence interval, could be used for point estimates of the main statistic under study. However, it is likely that the resulting sample sizes will either be impractically large or the bounds will include 0. If a researcher does not feel they can identify a suitably similar study, or if a researcher does not feel capable of developing an accurate effect size estimate, instead of using a pilot study researchers should be aware of the alternative methods for estimating effect sizes for power analysis that exist.

### Approach 2: Smallest Effect Size of Interest

“Ideally, a study should be large enough to have a high probability (power) of detecting as statistically significant a clinically important difference of a given size if such a difference exists” CONSORT statement on selecting sample sizes for research (Moher et al., 2010, p. e10).

A more cautious approach to effect size selection than attempting to estimate the “true” effect size under study is to use sample size estimates based not on an estimate of the true effect, but rather to use the minimum effect size of theoretical, practical or clinical significance (or the Smallest Effect Size of Interest, SESoI). This is the method of sample size determination that leads to the largest sample sizes being determined in the AiPE or power analysis frameworks. If used in power analyses this approach means that if an effect as or larger than the smallest effect of interest is present it will be detected at a chosen probability or higher. Arguably, this is the most internally coherent and reliable method of selecting a sample size, as unlike the above method, it does not rely on estimating an unknowable parameter, but rather in transparently making a subjective decision about the effect size that is minimally clinically or substantively important. None of the articles examined in Psychological Science explicitly noted that they were planning for the smallest effect of interest.

#### Selecting a Smallest Effect Size of Interest

The selection of the smallest effect size of interest has recently been discussed in the psychology literature in discussions around equivalence testing (i.e., statistical testing to investigate whether an effect is significantly smaller than the SESOI; see Lakens, 2017; or Lakens, Scheel, & Isager, 2018 for an extended discussion of the process of selecting a SESOI). Briefly, the smallest effect of interest can be specified in terms of unstandardized units (i.e., in raw scores on a given measure) or standardised units (e.g., in Cohen’s *d* or ), depending on what can meaningfully be justified and the researcher’s background knowledge. The SESOI can be justified on purely subjective grounds (e.g., by a researcher deciding that they do no feel an effect of 5 points on some scale or a Cohen’s *d* of .1 is not interesting to them), or in more objective terms (Lakens et al., 2018).

Selection of the SOSOI based on ‘objective’ standards has been most discussed in the clinical medicine literature. In medicine, finding the SESOI has two ends, one is in sample size planning, and the other is in determining what level of improvement would suggest that a change in treatment is advisable (Jaeschke, Singer, & Guyatt, 1989). One method of SESOI justification from the medical literature is the Minimal Detectable Difference (MDD), equivalent to the idea of detection thresholds in psychophysics (Norman, Sloan, & Wyrwich, 2003). The MDD acts as a reasonable SESOI in cases where scale score differences that cannot be consciously detected can reasonably be said to not be important. This is often the case in clinical research, where a treatment that does not cause a perceptible decrease in symptoms is unlikely to be worth prescribing (Jaeschke et al., 1989). Other methods of determining the SESOI in the clinical literature that have been suggested include examining population level differences (Norman et al., 2003), and attempting to identify cut scores that can reliably predict other objective consequences (e.g., rehospitalisation). In non-clinical areas of the behavioural sciences, additional ‘objective’ justifications could be found in theoretical model predictions (e.g., when theories are well developed enough to make point or interval predictions), or by external constraints (e.g., if an educational intervention will only be implemented if it raises scores by 10%).

#### Issues with the SESOI approach to sample size planning

Ensuring that a study has adequate sample sizes to reliably detect a minimum effect of interest can be particularly problematic in psychology research. Deciding on a minimum effect size can be extremely difficult, especially in non-applied or basic research where any non-zero effect may be theoretically interesting. The sample size required to reach a given level of power can be made arbitrarily large as the effect size of interest is decreased (Neyman & Pearson, 1933), meaning that if the effect size of interest is “any non-zero effect” it will be impossible for a study to appear to be adequately powered using this approach.

Although this may be the most conservative approach, its universal application could lead to counterproductive outcomes. Some of the most important research would seem prohibitively expensive if this approach was always used, as the smaller the effect size of interest, the larger and more expensive performing “adequately powered” (according to the SESOI approach) studies would be. This seems likely to be the case for interventions where outcomes of interest may be low frequency but high impact (e.g., mortality or severe mental illness) and areas of research where research may have large and important societal outcomes. In situations where there is reason to think that larger effect should be expected, ensuring that a study is adequately powered to detect a minimum interesting effect will be an extremely inefficient use of resources. However, in cases where the marginal cost of additional participants is low and a reasonable SOSOI can be determined, this approach provides guarantees that the experiment is likely to provide meaningful evidence or adequate precision given that an effect at least as large as the SESoI is present.

### Approach 3: Bayesian prior distribution

The final approach to effect size selection is to not specify a single alternative hypothesis, as is the case in the SESoI and effect size estimation approaches, but rather to use Bayesian prior distribution over effect sizes. If a Bayesian prior distribution is used to plan for frequentist statistical methods, this approach is often called planning for “assurance” (O'Hagan, Stevens, & Campbell, 2005). In the assurance approach, the prior distribution can represent the subjective probability of a researcher, that of a stakeholder or funder, or even a sceptical straw-man (Chen, Fraser, & Cuddeback, 2018). In the assurance approach, the prior distribution does not represent the expected effects under the alternative hypothesis, but rather a probability distribution over possible effect sizes, including the assigned probability of the null being true. The goal of assurance, the value that this approach estimates, is different from the approaches detailed above. Assurance no longer provides an estimate of the probability of obtaining statistical significance under the alternative hypothesis (or of obtaining sufficiently precise confidence intervals as in the case of AIPE), but instead estimates the probability of a researcher’s goals (e.g., statistical significance or sufficiently narrow CIs) being met given the specified prior distribution. The calculation of assurance under a specified prior distribution can be computationally complex, but reasonably easily implementable tools and methods have been developed (see Beavers & Stamey, 2018).

#### Bayesian sample size planning

If researchers are planning to perform Bayesian statistical analysis, there are a number of different approaches to sample size planning. One method, developed by Schönbrodt and Wagenmakers (2017) is to plan a sample size based on the probability of obtaining sufficiently compelling and accurate Bayes factors, or Bayes Factor Design Analysis. In their approach a researcher must specify a design prior (distribution of expected effect sizes) under the null and alternative hypotheses. The researcher must also specify an analysis prior (a prior which will be used in the statistical analysis, e.g., a prior distribution designed to convince a sceptical audience). Random samples are then simulated from the Design priors for the null and alternative hypotheses, and Bayes Factors are computed using the analysis prior (Schönbrodt and Wagenmakers suggest repeating this “say, 10,000 times”). A researcher can then select an appropriate design based on an assessment how often a design provides compelling evidence (e.g., BF > 10) under the null and alternative hypotheses at different sample sizes, and choose a sample size that maximises classification accuracy (Schönbrodt & Wagenmakers, 2017).

Another approach to Bayesian sample size determination is to specify a probability distribution over possible parameter values from the posterior distribution of an analysis of previous real or idealised data. The analyst can then sample parameter values (e.g., means and SDs) from the parameter value distribution, generate a set of simulated data, perform their statistical test on the simulated data, and check to see whether a particular goal condition has been met (e.g., sufficiently precise estimates, a sufficiently high or low Bayes factor, etc) (Kruschke & Liddell, 2017). Bayesian power analysis has the added benefit of accounting for uncertainty in parameter estimates, as opposed to the frequentist methods which tend to ignore this issue.

#### Issues with the Bayesian approaches to sample size determination

These tools are more flexible than their frequentist equivalents, and may be essential for planning research, budgeting, and in writing grant proposals when Bayesian analyses will be used for data-analysis. However, all of these methods, including the quasi-Bayesian assurance approach, require the specification of at least a design prior, the development of which is often a difficult task, and all currently require a level of technical expertise that is greater than that required in frequentist sample size planning where point-and-click interfaces are available. However, a number of tools have been already developed to enable researchers to develop reasonable prior distributions (e.g., Morris, Oakley, & Crowe, 2014), and it seems likely that more user friendly programs for Bayesian sample size planning (and analysis) will be developed as this approach to statistical analysis becomes more common (van de Schoot, Winter, Ryan, Zondervan-Zwijnenburg, & Depaoli, 2017).

### Conclusion

The most appropriate type of sample size planning will differ according to the desires of the researcher and the type of analysis to be performed. The great majority of studies which specified their effect size section method used methods that are likely to lead to mean levels of power that are below the optimal level on the basis of sampling variability along (e.g., using the effect from a single previous study). This issue that is compounded by publication bias which leads to inflated effect sizes in the published literature (Perugini et al., 2014). Given that the majority of published papers used methods that imply they were aiming to estimate the true power of studies, and the infrequency with which articles attempted to deal with publication bias in deriving effect sizes it is clear that researchers should at least be aware of the breath of methods available for sample size planning and the tools which have been developed to adjust effects for sampling variability and/or publication bias (see Anderson et al., 2017; McShane & Böckenholt, 2016; Perugini et al., 2014; and Taylor & Muller, 1996). If these methods are too difficult to implement, a simple heuristic suggested in Camerer et al. (2018) and [chapter pub bias] is to reduce the observed effects by 50%.

It is also worth noting that although these papers did not universally present results for which null hypothesis significance testing makes sense, all which provided any justification for the sample size they used justified their samples sizes used a power analysis. In many cases, using the AIPE approach to sample size planning, planning studies for estimate precision (or the equivalent in a Bayesian framework), would make more sense. For example, when estimating correlational relationships among personality traits, an area where the population effect size is almost certaintly a non-zero effect, a researcher is likely much more interested in precisely estimating the size and direction of the effect than merely testing the null hypothesis of r ≠ 0. See Maxwell et al. (2008) for a readable introduction to this approach.

Although focus has often been placed on increasing the sample size of research to increase power (e.g., Cohen, 1962 which relagates mention of other methods of increasing power to a footnote), other methods of increasing the power of statistical tests exist. Reducing measurement error, error variance, using repeated measures designs, increasing the alpha level, or increasing the size of the effect will lead to higher effect sizes and commensurately power in most cases (Loken & Gelman, 2017; Müller & Szegedi, 2002). One reason these other methods are often ignored is that these other elements are often assumed to be fixed by custom, already be optimised for maximum power, or difficult for the researcher to alter (Cohen, 1962). The alpha level used (which also impacts statistical power) is almost never changed, and then almost only ever made more strict leading to lower power (Gigerenzer, 2004). The effect size tends to be considered fixed, or assumed to already be maximized (Lakens & Evers, 2014). Other parameters (e.g., correlations between repeated measurements) are often thought to be outside of a researcher’s control. However, the experimental design will often be alterable (i.e., it may be possible to use a repeated measures design as opposed to a between subjects design), and it may be possible to prioritize obtaining highly reliable measures of constructs under study in order to maximize effect sizes (by reducing measurement error) and increasing power.

In cases where it is particularly difficult to specify an effect size on a priori grounds, a reasonable approach may be to figure out the maximum sample size that can be recruited and use this value to perform a sensitivity analysis, estimating the effect size that can be detected at a goal level of statistical power or with adequate precision. Equivalently, the power curve of an analysis (the power of the test over a range of possible population effect sizes given the maximum sample size achievable) could be examined in order for the researcher to understand the effect of different effect sizes on the statistical power of an analysis. If the effect sizes required to achieve adequate power or precision are larger than you believe are likely or possible at the maximum sample size that is recruitable, it may not be advisable to not perform an experiment.

Finally, if an experiment is going to be performed which is likely to be underpowered or insufficiently precise, it becomes acutely important to ensure that the data will be available to future meta-analysts regardless of the statistical significance of results. Access to these imprecise estimates or non-significant results may be essential for the accurate estimation of effect sizes (Anderson et al., 2017). Thankfully, newly developed tools such as pre-print servers like psyarxiv.com or data-repositories like figshare (figshare.com) and the Open Science Framework (osf.io), are now available. These services mean it is now possible for researchers to make your data and the results of analyses available and discoverable outside of the traditional publication system, making it is possible to circumvent the traditional system’s apparent aversion to non-significant results.

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