# x.1 How to choose effect sizes for sample size determination

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 are required to specify the effect size and other parameters that are required for power analysis. There are two commonly used approaches reported by psychologists, estimating the expected effect size (Anderson, Kelley, & Maxwell, 2017), using the minimum interesting or clinically significant effect size (Biau, Kernéis, & Porcher, 2008) and using estimates from pilot studies (Albers & Lakens, 2018). A fourth 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 be ‘successful’ based on an author’s outcome criteria (Ren & Oakley, 2014), or the probability of developing convincing evidence or precise interval estimates in Bayesian analyses.

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 chapter outlines these different approaches to selecting effect sizes in formal power analysis and clearly explains the implications of each approach, as well as reinforcing the warnings that have been provided against using effect size estimates from pilot studies.

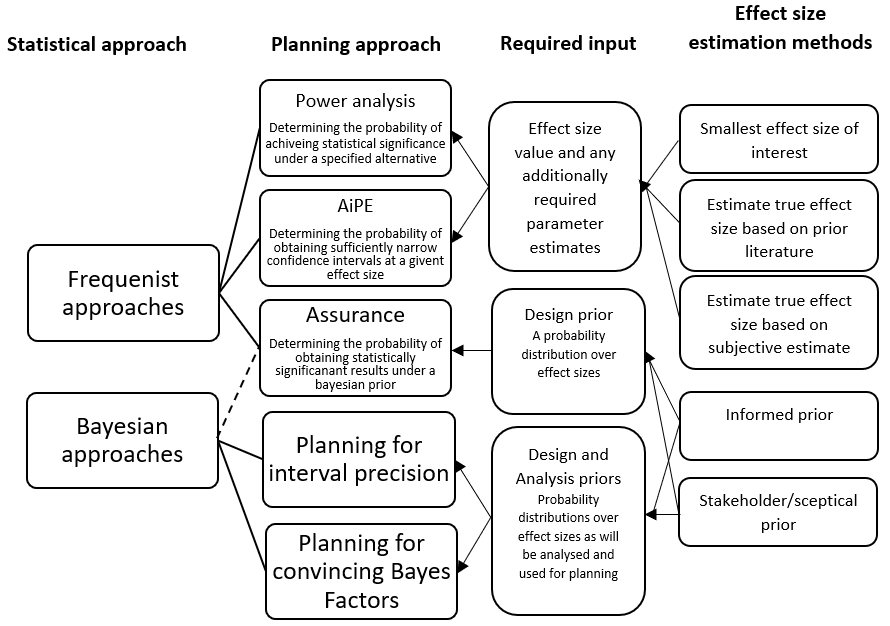


Figure [approaches to formal sample size planning]. Figure showing the different approaches to effect size estimation determination in different statistical frameworks.

## Terms

Box [Definitions]

Power analysis

Accuracy in Parameter Estimation (AiPE)

Bayesian Design Prior

Bayesian Analysis Prior

Sampling distribution

The probability distribution of a random variable under a given

Test statistic

## 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 statistical analysis approach 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 given statistical analysis, the true effect size is never known and these different approaches to estimating effect sizes for power analysis lead to very different interpretations of the estimated statistical power of analyses. It is arguable that there is no single true effect size on an a priori basis, as the small differences in variability in methods, situation and population sampled from will impact the unknown true effect size at least to a minute degree. The current paper focuses on the final level of Figure [approaches to formal sample size planning], on the different approaches to developing effect size estimates for use in power analysis, giving straightforward advice on how an interested researcher can meaningfully develop effect size estimates for use in a power analysis.

### Method 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 true effect size, 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 x% (a value commonly and arbitrarily set at 80%) of occasions. 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.

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). As this is the only method of sample size determination that involves estimating the true effect size of the planned study, 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, formal sample size planning is of little use, as any sample size greater than one has 80% power to detect a large enough effect size. This means that 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.

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 non-central aspects of the pilot study to inform aspects of sample size planning (e.g., using the upper bound of a 95% CI as an estimate of the standard deviation of a random variable). This same approach could be used for point estimates of the statistic under study, but it is likely that the resulting sample sizes will either be impracticably large or the bounds will include 0 suggesting that the sample size required would be approximately infinite.

#### 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 provides a direct or reasonable estimate of the true effect size of the effect under study, although even then it may 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. See chapter [effect size measures] for definitions of the most commonly required effect sizes are, and of how they can be extracted from more commonly reported test statistics and effect sizes.

The degree to which selection of an adequately similar body of research is likely to be a problem is a complicated issue in that the more novel the experiment, the less indicative previous effects sizes may be of the current study’s likely effect, and the degree of difference that could be expected is a matter of judgement. Because of this fact, in the great majority of cases these types of power analyses act not as estimates of the true power of a study, but as a demonstration that the study was adequately powered to detect reasonably similar types of effects, thus likely able to reliably detect a reasonable person’s guess of the study’s effect if there was an effect. If the researcher conducting the experiment had a high degree of confidence in the estimated effect based on previous research, they would likely not perform the planned experiment.

#### Accounting for effect size imprecision and exaggeration

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). Even ignoring publication bias imprecision in parameter estimates can be problematic, using effect sizes directly from previous literature will lead to power estimates inflating the apparent power approximately 50% of the time simply on the basis of sampling variability alone (Taylor & Muller, 1996). 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). Evidence from projects that have systematically attempted to reproduce bodies of psychology research suggest that the impact of publication and reporting biases may be to increase reported effects by as much as 30 – 50% (Camerer et al., 2018; Open Science Collaboration, 2015). 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 publication bias and the sample variability inherent point estimates of effects sizes or parameters (see Anderson et al., 2017; McShane & Böckenholt, 2016; Perugini, Gallucci, & Costantini, 2014; and Taylor & Muller, 1996). Camerer et al. (2018) suggest simply halving effect size estimates from the published literature to arrive at a reasonable estimate of the true effect size.

It may not be uncommon for a researcher performing novel research to not to feel capable of identifying a sufficiently similar set of studies for a power analysis to be meaningfully performed. If a researcher does not feel capable of developing an accurate effect size estimate, a conservative estimate can be used to ensure that a planned study will be able to reliably detect a lower bound estimate of the effect if it is in fact present.

### 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 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. 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 theoretically meaningful 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.

**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 psychology research, 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 this approach**

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 to detect the minimum effect of interest. Furthermore, 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 extremely inefficient.

Although this may be the most conservative approach, its strict application would lead to some of the most important research seeming prohibitively expensive and never being performed. Given that areas of research where small effects are be of particular interest, for example in interventions where outcomes of interest may be low frequency but high impact (e.g., mortality or severe mental illness), a large proportion of these studies would appear to require such high sample sizes so as to be impossible to practically perform, despite the fact that reasonably well-powered experiments may be possible given the unknown true impact of a set of interventions. However, in cases where the marginal cost of additional participants is low and reasonable SOSOI can be determined, this approach provides assurance that the experiment is likely to provide meaningful evidence or adequate precision given that the minimum effect 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 methods for sample size planning. If a Bayesian prior distribution is used to plan for frequentist statistical methods, this approach is often called “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 the researchers’ prior distribution including their assigned probability for the null being true. The goal of assurance, the value that this approach estimates, is different from the above approaches. Assurance no longer provides an estimate of the probability of obtaining statistical significance under the null 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, or even correct classification of the presence or absence of effects using more complex decision rules) 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 (Beavers & Stamey, 2018).

**Bayesian sample size planning**

If researchers are planning to perform Bayesian statistical analysis, Schönbrodt and Wagenmakers (2017) developed a method to plan for sample size planning for sufficiently compelling and accurate Bayes factors. In their approach a researcher must specify a design prior (distribution of expected effect sizes) under the null, as well as the 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 under the null and alternative hypotheses (Schönbrodt & Wagenmakers, 2017).

Another approach to Bayesian sample size determination is to specify a probability distribution over possible parameter values often generated from the posterior distribution from a previous analysis of real or idealised data. Using Markov chain Monte Carlo sampling, the analyst can then sample parameter values (e.g., means and SDs) from the parameter value distribution, generate a set of simulated data, test 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.

A number of tools have been developed to enable researchers to develop reasonable prior distributions. TOOL FOR EXPERT ELICITATION - - - (Morris, Oakley, & Crowe, 2014)

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| **Approach to effect size selection** | **Implication** |
| Smallest effect size of interest (SESoI) | Effect sizes as large or greater than the smallest effect size of interest have at least the chosen probability of being detected |
| Estimated true effect | Effect sizes as large or greater than the estimated size of interest have at least the chosen probability of being detected. Only as accurate as the effect selected. |
| Bayesian prior distribution (assurance) | Gives the probability of obtaining a set of statistical results (often statistical significance) given a Bayesian prior distribution over possible parameter values. Only as accurate as the prior distribution. |

**Current practices**

In order to get an initial sense of they types of practices common in psychology I assessed the July and August 2018 issues of Psychological Science. The sample is not representative of psychology articles in general, and the estimates are not precise enough to make any claims about the general trends in the examined journal. Of the 30 empirical research articles published in this period 50% (n = 15) reported a power analysis. Of the reported power analyses, the most common approach (used in 9 of 15 cases) was to estimate the true effect of the intervention. Most of these articles used a point estimate from a single previous study (n = 6) to estimate the effect of an intervention. Just two articles reported using effect sizes from meta analyses toward the same goal, and one used the effect size seen in a pilot study. The other articles either reported a sensitivity analysis (showing the effect size that the sample size gave them 80% power to detect, n = 3) in order to justify the obtained sample size, or they used benchmarks from Cohen (1988; n = 2) or did not provide any justification for the effect size used in power analysis (n = 1), making it unclear whether their estimate was of the minimum effect of interest or an estimate of the true effect size of the intervention (see <https://osf.io/bmv2d/> for the data behind the above description).

There are several possible reasons for the scarcity of Assurance calculations in psychological research. Firstly, researchers appear to rarely use any of the more complex approaches to These methods are rarely used, 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.

**3.8 Increasing precision or power without increasing the sample size included in a study**

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 (my reducing measurement error) and increasing power.

This paper has not considered other approaches to sample size planning that do not require estimation of the effect size

There are other suggested approaches to sample size planning that do not

Equivalently, an examination of the power curve of an analysis (the power of the test over a range of possible population effect sizes) could be examined in order for the researcher to understand the range of possible effect sizes that are reliably detectable in order to decide whether it is advisable for an experiment to be conducted

A reasonable approach may be to figure out the maximum sample size that you can recruit and use this value to perform a sensitivity analysis (varying any other parameters that must be set or placing them at conservative estimates), estimating the effect size that can be detected at a goal level of statistical power. If the estimated effect size seems larger than you believe is likely or possible, consider not performing the experiment. If the experiment is going to go on in any case, take care to ensure that the results will be available to meta-analysts and other researchers regardless of the statistical significance of results (e.g., by posting results on a publicly searchable archive like psyarxiv.com), and ensure that the analysis plan is pre-registered in order to allow yourself to distinguish between the pre-planned confirmatory analyses and any future exploratory analysis. Given the pressure that researchers are under to publish, it seems intuitively plausible that

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