PREPRINT

Exploring Equivalence Testing with the Updated TOSTER R Package

Aaron R. Caldwell[a]

[a]Natick, MA, https://orcid.org/0000-0002-4541-6283

ARTICLE HISTORY
Compiled November 15, 2022

ABSTRACT
Equivalence testing is arguably under utilized by experimental researchers. Despite decades of published statistical crititques, researchers seems unable or unwilling to implement such equivalence testing procedures. This may be due to limited software support for such analyses and little education on the topic in graduate programs. One option for equivalence testing is two one-sided tests (TOST). The TOSTER R package and jamovi module, originally developed by Daniel Lakens in 2017, was created to make TOST more accessible to the average researcher. In the past two years, I have made significant changes to the TOSTER package in order to increase its accessibility and provide more robust analysis options for researchers. In this paper, I will detail the changes to the package and highlight new analysis options that will make TOST easier for the average quantitative researcher.

KEYWORDS
statistics, bootstrap, minimal effects test, NHST, TOST

1. Introduction

Researchers often erroneously declare that no statistical effect exists based on a single "non-significant" p-value (Altman and Bland 1995). In many of these cases, the data may corroborate the researchers claim but the interpretation of a null hypothesis significance test (NHST), wherein the null hypothesis is "no effect", is nonetheless incorrect. In order to statistically test for whether there is "no effect" or "no difference" researchers could explore using equivalence testing. A very simple equivalence testing approach is the use of "two one-sided tests" (TOST) (Schuirmann 1987). In TOST procedures, an upper (Δ_U) and lower (Δ_L) equivalence bound is specified based on the smallest effect size of interest (SESOI). If the TOST is below a pre-specified alpha level, then the effect can be considered close enough to zero to be practically equivalent (Lakens 2017).

Both the complaints about erroneous conclusions regarding equivalence (Altman and Bland 1995) and proposed statistical solutions (Schuirmann 1987) have existed for decades now. Yet the problem appears to persist in many applied disciplines. I estimate that the cause of this continued dissonance is due to a lack of education on equivalence testing and a struggle for many applied researchers to implement equivalence testing. In my experience, most researchers have received some degree of statistical training

CONTACT Aaron R. Caldwell. Email: arcaldwell49@gmail.com

in their doctoral or master's studies, but it is rare that any have idea of how to use TOST. It may also be difficult to implement equivalence testing for many researchers. This may be caused by most statistical software defaulting to a null hypothesis of zero, or even completely lacking an ability to change the null hypothesis. Therefore, I feel continued development of educational content on TOST, and software to help with such analyses, would be beneficial to many quantitative researchers.

The TOSTER R package[1] was originally developed in by Lakens (2017) to introduce experimental psychologists to the concept of equivalence testing and provide an easy-to-use implementation in R. In the years since that publication, I have made a significant update to the package in order to improve the user interface and expand the tools available within the package. An experienced R programmer may have no problem performing equivalence testing within R but beginners may struggle with both writing the code and interpreting the output. If you fall into that category, I would suggest using `jamovi`, an open-source statistical software, that has a TOSTER module to perform equivalence/TOST analyses.

In this manuscript, I will detail the updates to the TOSTER package, and give some basic usage examples of some of the new functions. This is meant to just be an introduction to *how* to perform such analyses, and provide a little bit of context for when such analyses are appropriate. For a greater introduction to equivalence testing, I would suggest reading other methodological tutorials (Lakens 2017; Lakens, Scheel, and Isager 2018; Lakens et al. 2020; Mazzolari et al. 2022).

2. TOST with t-tests

In an effort to make TOSTER more informative and easier to use, a new function `t_TOST` was created. This function operates very similarly to base R's `t.test` function, but performs 3 t-tests (one two-tailed and two one-tailed tests). In addition, this function has a generic method where two vectors can be supplied or a formula can be given (e.g.,`y ~ group`). This function also makes it easier to switch between types of t-tests. All three types (two-sample, one-sample, and paired samples) can be performed/calculated from the same function. Moreover, the output from this function is verbose, and should make the decisions derived from the function more informative and user-friendly.

Also, `t_TOST` is not limited to equivalence tests. Minimal effects testing (MET) is possible. MET is useful for situations where the hypothesis is about a minimal effect and the null hypothesis *is* equivalence (see Figure 1).

[1] All updates to the package can be found on the package's website `https://aaroncaldwell.us/TOSTERpkg`

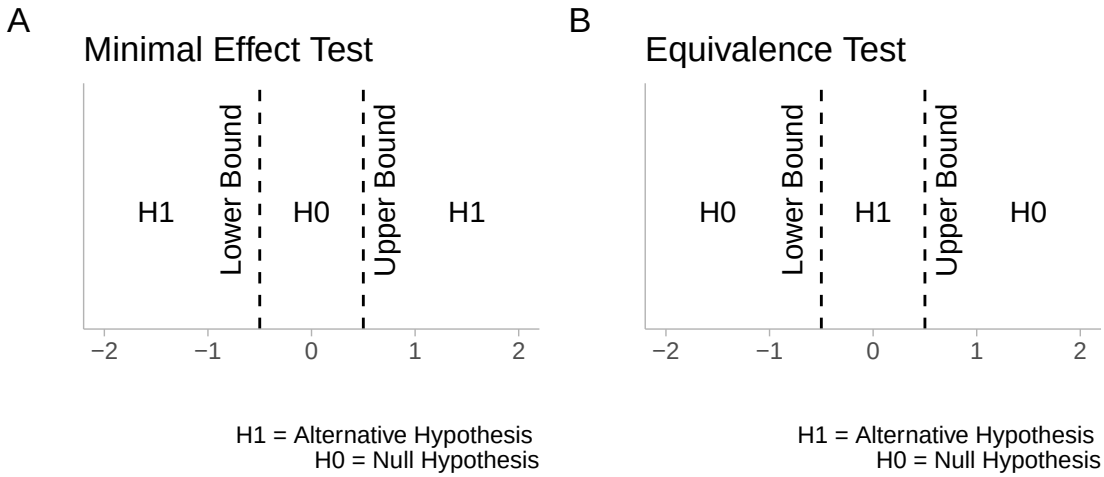

Figure 1. Type of Hypothesis

In the general introduction to this package we detailed how to look at *old* results and how to apply TOST to interpreting those results. However, in many cases, users may have new data that needs to be analyzed. Therefore, `t_TOST` can be applied to new data. This vignette will use the `bugs` data from the `jmv` R package and the `sleep` data.

```
data('sleep')
library(jmv)
data('bugs')
```

2.1. *Independent Groups*

For this example, we will use the sleep data. In this data there is a `group` variable and an outcome `extra`.

```
head(sleep,2)
```

```
##   extra group ID
## 1   0.7     1  1
## 2  -1.6     1  2
```

We will assume the data are independent, and that we have equivalence bounds of +/- 0.5. All we need to do is provide the `formula`, `data`, and `eqb` arguments for the function to run appropriately. In addition, we can set the `var.equal` argument (to assume equal variance), and the `paired` argument (sets if the data is paired or not). Both are logical indicators that can be set to TRUE or FALSE. The `alpha` is automatically set to 0.05 but this can also be adjusted by the user.

Standardize mean differences (SMDs) are provided in the output for any t-test based TOST analysis (e.g., Cohen's d). The Hedges's corrected SMD (Hedges 1981) is automatically calculated, but this can be overridden with the `bias_correction`

argument[2]. In previous versions of this package, the equivalence bounds could be set by the SMD (e.g., equivalence bound of 0.5 SD), but this is an erroneous approach since the bound would be dependent upon the *sample* variance. However, users can opt for such an analysis by setting `eqbound_type` to SMD, which will produce a noticeable warning to the R console.

The `hypothesis` argument is automatically set to "EQU" for equivalence but if a minimal effect is of interest then "MET" can be supplied.

```
# Formula Interface
res1 = t_TOST(formula = extra ~ group, data = sleep,
              eqb = .5, smd_ci = "t")
# x & y Interface
res1a = t_TOST(x = subset(sleep,group==1)$extra,
               y = subset(sleep,group==2)$extra, eqb =.5)
```

Once the function has run, we can print the results with the `print` method. This provides a verbose summary of the results.

```
print(res1)
```

```
##
## Welch Two Sample t-test
##
## The equivalence test was non-significant, t(17.78) = -1.272, p = 8.9e-01
## The null hypothesis test was non-significant, t(17.78) = -1.861, p = 7.94e-02
## NHST: don't reject null significance hypothesis that the effect is equal to zero
## TOST: don't reject null equivalence hypothesis
##
## TOST Results
##                 t    df p.value
## t-test     -1.861 17.78   0.079
## TOST Lower -1.272 17.78   0.890
## TOST Upper -2.450 17.78   0.012
##
## Effect Sizes
##                Estimate     SE               C.I. Conf. Level
## Raw             -1.5800 0.8491 [-3.0534, -0.1066]         0.9
## Hedges's g(av)  -0.7965 0.5992  [-1.8362, 0.2433]         0.9
## Note: SMD confidence intervals are an approximation. See vignette("SMD_calcs").
```

[2]Glass's delta can also be produced in the output by using the `glass` argument

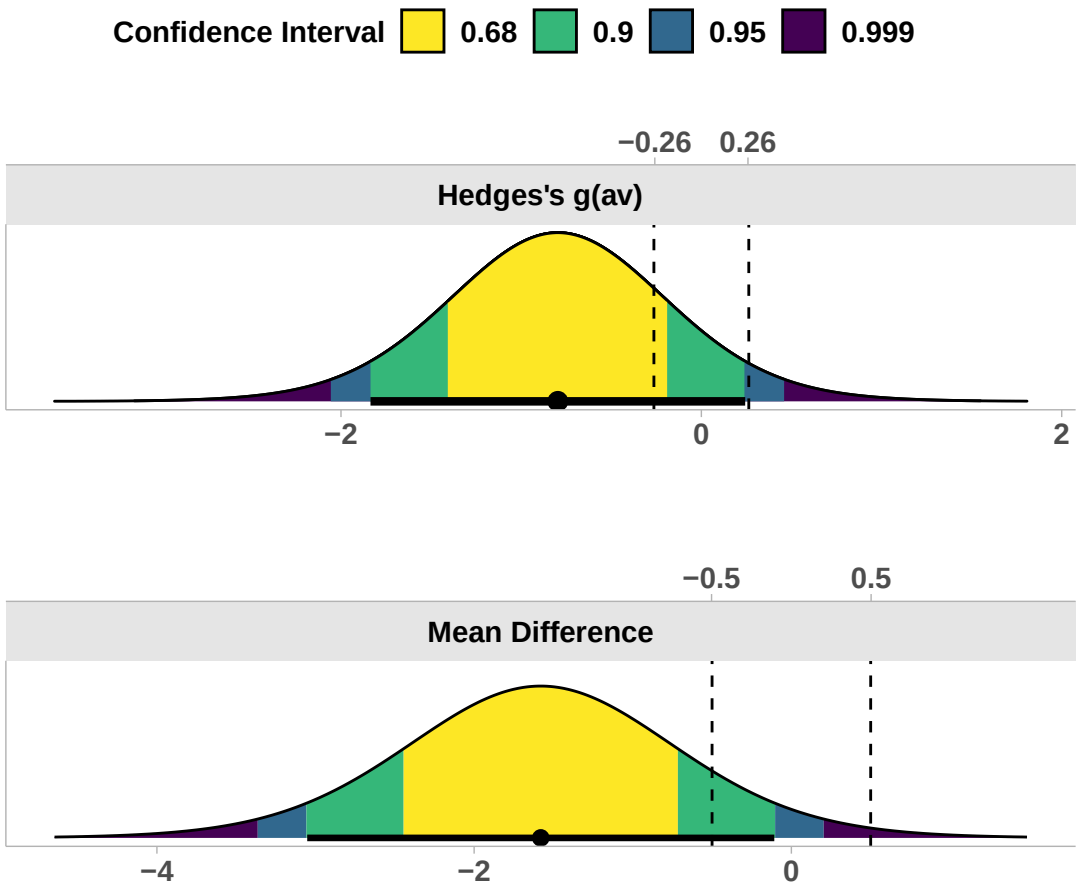

Figure 2. Example of consonance density plot.

Another nice feature is the generic `plot` method that can provide a visual summary of the results. All of the plots in this package were inspired by the concurve R package. There are two types of plots that can be produced. The first, and default, is the consonance density plot (`type = "cd"`).

```
plot(res1, type = "cd")
```

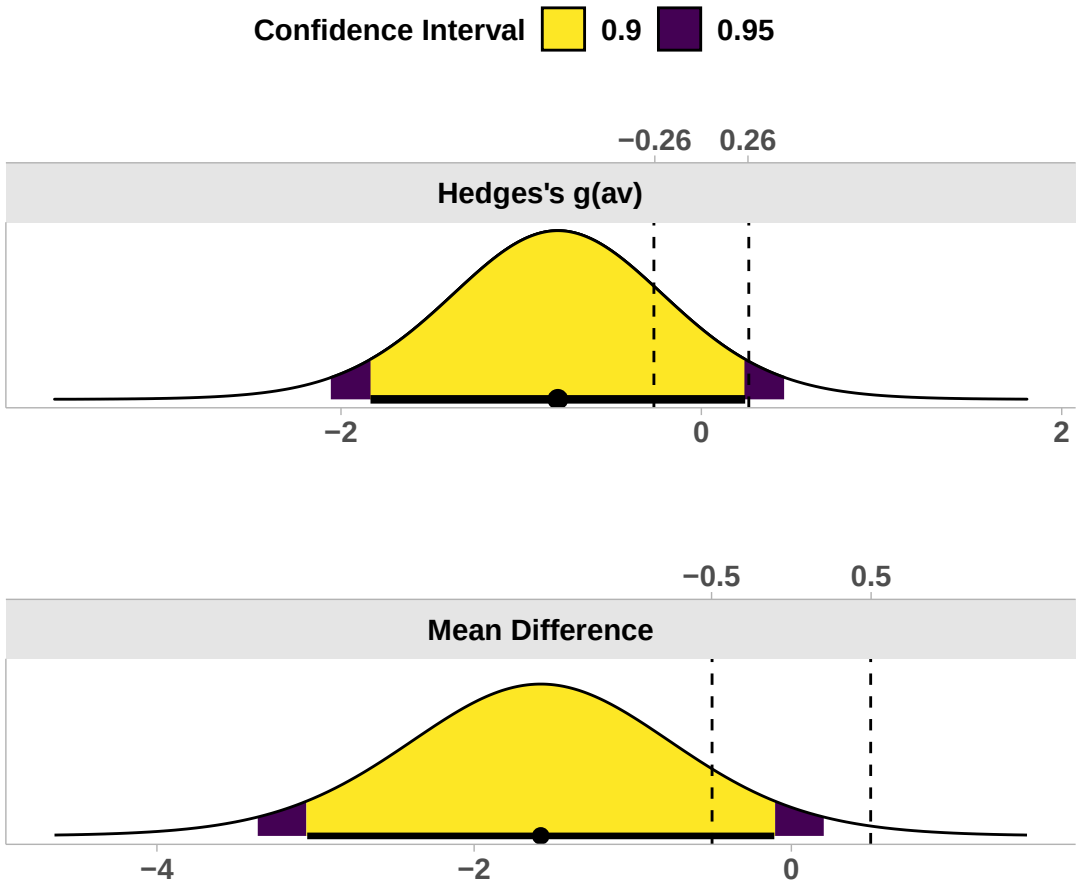

Figure 3. Demonstrating the shading in plot method.

The shading pattern can be modified with the `ci_shades`.

```
plot(res1, type = "cd",
     ci_shades = c(.9,.95))
```

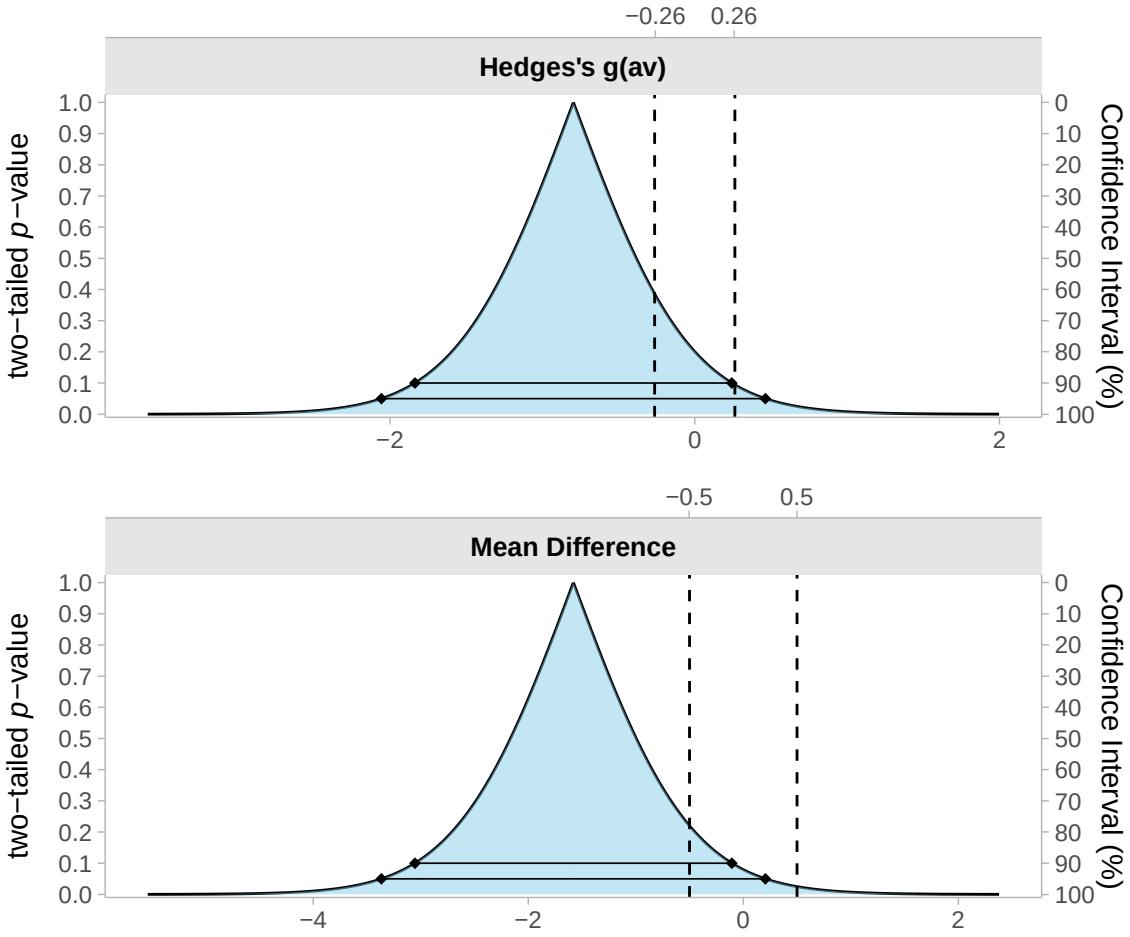

Figure 4. Example of consonance plot.

Consonance plots, where all confidence intervals can be simultaneous plotted, can also be produced. The advantage here is multiple confidence interval lines can plotted at once.

```
plot(res1, type = "c",
     ci_lines =  c(.9,.95))
```

2.2. *Paired Sample*

To perform TOST on paired samples, the process does not change much. We could process the test the same way by providing a formula. All we would need to then is change `paired` to TRUE.

```
res2 = t_TOST(formula = extra ~ group,
              data = sleep,
              paired = TRUE,
              eqb = .5)
res2
```

```
##
## Paired t-test
##
## The equivalence test was non-significant, t(9) = -2.777, p = 9.89e-01
## The null hypothesis test was significant, t(9) = -4.062, p = 2.83e-03
## NHST: reject null significance hypothesis that the effect is equal to zero
## TOST: don't reject null equivalence hypothesis
##
## TOST Results
##                 t df p.value
## t-test     -4.062  9   0.003
## TOST Lower -2.777  9   0.989
## TOST Upper -5.348  9 < 0.001
##
## Effect Sizes
##               Estimate    SE               C.I. Conf. Level
## Raw             -1.580 0.389   [-2.293, -0.867]         0.9
## Hedges's g(z)   -1.174 0.411 [-1.8046, -0.4977]         0.9
## Note: SMD confidence intervals are an approximation. See vignette("SMD_calcs").
```

However, we may have two vectors of data that are paired. So instead we may want to just provide those separately rather than using a data set and setting the formula. This can be demonstrated with the "bugs" data.

```
res3 = t_TOST(x = bugs$LDHF,
              y = bugs$LDLF,
              paired = TRUE,
              eqb = 1)
res3
```

```
##
## Paired t-test
##
## The equivalence test was non-significant, t(90) = 2.655, p = 9.95e-01
## The null hypothesis test was significant, t(90) = 6.649, p = 2.22e-09
## NHST: reject null significance hypothesis that the effect is equal to zero
## TOST: don't reject null equivalence hypothesis
##
## TOST Results
##                 t df p.value
## t-test      6.649 90 < 0.001
## TOST Lower 10.642 90 < 0.001
## TOST Upper  2.655 90   0.995
##
## Effect Sizes
##               Estimate     SE             C.I. Conf. Level
## Raw             1.6648 0.2504  [1.2487, 2.081]         0.9
## Hedges's g(z)   0.6911 0.1167 [0.4987, 0.8802]         0.9
## Note: SMD confidence intervals are an approximation. See vignette("SMD_calcs").
```

We may want to perform a Minimal Effect Test with the `hypothesis` argument set to "MET".

```
res3a = t_TOST(x = bugs$LDHF,
               y = bugs$LDLF,
               paired = TRUE,
               hypothesis = "MET",
               eqb = 1)
res3a
```

```
##
## Paired t-test
##
## The minimal effect test was significant, t(90) = 10.642, p = 4.69e-03
## The null hypothesis test was significant, t(90) = 6.649, p = 2.22e-09
## NHST: reject null significance hypothesis that the effect is equal to zero
## TOST: reject null MET hypothesis
##
## TOST Results
##                 t df p.value
## t-test      6.649 90 < 0.001
## TOST Lower 10.642 90       1
## TOST Upper  2.655 90   0.005
##
## Effect Sizes
##               Estimate     SE             C.I. Conf. Level
## Raw             1.6648 0.2504  [1.2487, 2.081]         0.9
## Hedges's g(z)   0.6911 0.1167 [0.4987, 0.8802]         0.9
## Note: SMD confidence intervals are an approximation. See vignette("SMD_calcs").
```

2.3. *One-Sample t-test*

In other cases we may have a one-sample test. If that is the case, only `x` argument for the data is needed. As an example, we may hypothesis that the mean of LDHF is not more than 1.5 points greater or less than 7.

```
res4 = t_TOST(x = bugs$LDHF,
              hypothesis = "EQU",
              eqb = c(5.5,8.5))
res4
```

```
##
## One Sample t-test
##
## The equivalence test was significant, t(90) = -4.244, p = 2.66e-05
## The null hypothesis test was significant, t(90) = 27.942, p = 3.91e-46
## NHST: reject null significance hypothesis that the effect is equal to zero
## TOST: reject null equivalence hypothesis
##
## TOST Results
##                 t df p.value
## t-test     27.942 90 < 0.001
## TOST Lower  7.116 90 < 0.001
## TOST Upper -4.244 90 < 0.001
##
## Effect Sizes
##            Estimate     SE             C.I. Conf. Level
## Raw           7.379 0.2641  [6.9402, 7.818]         0.9
## Hedges's g    2.905 0.2395 [2.5058, 3.2949]         0.9
## Note: SMD confidence intervals are an approximation. See vignette("SMD_calcs").
```

2.4. *Using Summary Statistics*

In some cases you may only have access to the summary statistics (e.g., when reviewing an article or attempting to perform a meta-analysis). Therefore, I created a function, `tsum_TOST`, to perform the same tests just based on the summary statistics. This involves providing the function with a number of different arguments.

- `n1 & n2` the sample sizes (only n1 needs to be provided for one sample case)
- `m1 & m2` the sample means
- `sd1 & sd2` the sample standard deviation
- `r12` the correlation between each if paired is set to TRUE

The results from above can be replicated with the `tsum_TOST`:

```
res_tsum = tsum_TOST(
  m1 = mean(bugs$LDHF, na.rm=TRUE), sd1 = sd(bugs$LDHF, na.rm=TRUE),
  n1 = length(na.omit(bugs$LDHF)),
  hypothesis = "EQU", smd_ci = "t", eqb = c(5.5, 8.5)
)

res_tsum
```

```
##
## One-sample t-Test
##
## The equivalence test was significant, t(90) = -4.244, p = 2.66e-05
## The null hypothesis test was significant, t(90) = 27.942, p = 3.91e-46
## NHST: reject null significance hypothesis that the effect is equal to zero
## TOST: reject null equivalence hypothesis
##
## TOST Results
##                 t df p.value
## t-test     27.942 90 < 0.001
## TOST Lower  7.116 90 < 0.001
## TOST Upper -4.244 90 < 0.001
##
## Effect Sizes
##            Estimate     SE             C.I. Conf. Level
## Raw           7.379 0.2641  [6.9402, 7.818]         0.9
## Hedges's g    2.905 0.2395 [2.4289, 3.3804]         0.9
## Note: SMD confidence intervals are an approximation. See vignette("SMD_calcs").
```

3. Robust Methods for Equivalence Testing

In some cases, the use of t-test may be less than ideal. Any serious violation to the assumptions of a t-test (e.g., normality or homoscedasticity) could greatly inflate the type 1 error rate of TOST. Therefore, it may be useful to explore alternatives to the t-test for TOST.

The TOSTER package currently provides 4 robust alternatives to the t-test for TOST. First, there is the `wilcox_TOST` function which uses the Wilcoxon-Mann-Whitney (WMW) type tests (i.e., `wilcox.test`) to perform TOST as a test of symmetry. Second, there is the `log_TOST` function which performs log-transformed t-tests, which is a parametric approach commonly used in pharmaceutical bioequivalence studies on ratio data (He et al. 2022). Third, there is the `boot_t_TOST` function which uses the bootstrap method outlined by Efron and Tibshirani (1993). Fourth, there is the `boot_log_TOST` function which uses the same bootstrap method outlined by Efron and Tibshirani (1993) but on the log-transformed data, which is more robust than parametric log t-test (He et al. 2022).

In the following sections, I will briefly outline the available robust TOST functions within the TOSTER package.

3.1. *Tests of Symmetry (rank based tests)*

The WMW group of tests (e.g., Mann-Whitney U-test) provide a non-parametric test of differences between groups, or within samples, based on *ranks*. This provides a test of location shift, which is a fancy way of saying differences in the center of the distribution (i.e., in parametric tests the location is mean). Within the TOST framework, there are two separate tests of directional location shift to determine if the location shift is within (equivalence) or outside (minimal effect) the equivalence bounds. Many researchers mistakenly think these are tests of medians, but this is not the case (See Divine et al. (2018) for details). Using a WMW-based TOST is useful for testing whether the differences between groups/conditions is symmetric around the equivalence bounds[3]. For equivalence testing, the TOST would be testing whether there is asymmetry towards no effect with a null hypothesis of symmetry at the equivalence bound.

In the TOSTER package, we accomplish this "test of symmetry" with the `wilcox_TOST` function. This function operates in an extremely similar implementation to the `t_TOST` function. The exact calculations utilized in this function can be explored via the documentation of the `wilcox.test` function. A standardized mean difference (SMD) is *not* calculated in this function since this would be an inappropriate measure of effect size alongside the non-parametric test statistics. Instead, a standardized effect size (SES) is calculated for *all* types of comparisons (e.g., two-sample, one sample, and paired samples). The function can produce a rank-biserial correlation (Kerby 2014), a WMW Odds (O'Brien and Castelloe 2006), or a "common language effect size" (Kerby 2014) (Also known as the non-parametric probability of superiority, or concordance probability).[4]

As an example, we can use the sleep data to make a non-parametric comparison of equivalence.

[3] Care should be taken when considering paired samples; a test on the rank transformed data (Kornbrot 1990) or another robust test may be more prudent.

[4] There is no plotting capability at this time for the output of this function.

```
data('sleep')
library(TOSTER)

test1 = wilcox_TOST(formula = extra ~ group,
                    data = sleep,
                    paired = FALSE,
                    eqb = .5)


print(test1)
```

```
##
## Wilcoxon rank sum test with continuity correction
##
## The equivalence test was non-significant W = 20.000, p = 8.94e-01
## The null hypothesis test was non-significant W = 25.500, p = 6.93e-02
## NHST: don't reject null significance hypothesis that the effect is equal to zero
## TOST: don't reject null equivalence hypothesis
##
## TOST Results
##            Test Statistic p.value
## NHST                 25.5   0.069
## TOST Lower           34.0   0.894
## TOST Upper           20.0   0.013
##
## Effect Sizes
##                            Estimate               C.I. Conf. Level
## Median of Differences        -1.346       [-3.4, -0.1]         0.9
## Rank-Biserial Correlation    -0.490 [-0.7493, -0.1005]         0.9
```

3.2. *Bootstrap TOST*

The bootstrap refers to resampling with replacement and can be used statistical estimation and inference. Bootsrapping techniques are very useful because they are considered somewhat robust to the violations of assumptions for a simple t-test. Therefore we added a bootstrap option, `boot_t_TOST` to the package to provide another robust alternative to the `t_TOST` function.

In this function we provide a percentile bootstrap solution outlined by Efron and Tibshirani (1993) (see chapter 16, page 220). The bootstrapped p-values are derived from the "studentized" version of a test of mean differences (Efron and Tibshirani 1993). Overall, the results should be similar to the results of `t_TOST`. **However**, for paired samples, the Cohen's d(rm) effect size *cannot* be calculated by this function.

3.2.1. Two Sample Algorithm

1. Form B bootstrap data sets from x* and y* wherein x* is sampled with replacement from $\tilde{x}_1, \tilde{x}_2, ...\tilde{x}_n$ and y* is sampled with replacement from $\tilde{y}_1, \tilde{y}_2, ...\tilde{y}_n$
2. t is then evaluated on each sample, but the mean of each sample (y or x) and the overall average (z) are subtracted from each

$$t(z^{*b}) = \frac{(\bar{x}^* - \bar{x} - \bar{z}) - (\bar{y}^* - \bar{y} - \bar{z})}{\sqrt{sd_y^*/n_y + sd_x^*/n_x}}$$

3. An approximate p-value can then be calculated as the number of bootstrapped results greater than the observed t-statistic from the sample.

$$p_{boot} = \frac{\#t(z^{*b}) \geq t_{sample}}{B}$$

The same process is completed for the one-sample case but with the one-sample solution for the equation outlined by $t(z^{*b})$. The paired sample case in this bootstrap procedure is equivalent to the one-sample solution because the test is based on the difference scores.

3.2.2. Example of Bootsrapping

We can use the sleep data to see the bootstrapped results. If you plot the bootstrap samples, it will show how the resampling via bootstrapping indicates the instability of Hedges' d(z). Just looking at the printed results you will notice some differences between confidence intervals from the bootstrapped result and the t-test.

```
data('sleep')
set.seed(891111)
test1 = boot_t_TOST(formula = extra ~ group,
                    data = sleep,
                    paired = TRUE,
                    eqb = .5,
                    R = 999)


print(test1)
```

```
##
## Bootstrapped Paired t-test
##
## The equivalence test was non-significant, t(9) = -2.777, p = 1e+00
## The null hypothesis test was significant, t(9) = -4.062, p = 0e+00
## NHST: reject null significance hypothesis that the effect is equal to zero
## TOST: don't reject null equivalence hypothesis
##
## TOST Results
##                  t df p.value
## t-test     -4.062  9 < 0.001
## TOST Lower -2.777  9       1
## TOST Upper -5.348  9 < 0.001
##
```

```
## Effect Sizes
##                Estimate     SE                C.I. Conf. Level
## Raw              -1.580 0.3699    [-2.26, -1.038]         0.9
## Hedges's g(z)    -1.174 0.6491 [-2.7507, -0.9285]         0.9
## Note: percentile bootstrap method utilized.
```

3.3. *Log TOST*

The natural logarithmic (log) transformation is often utilized to stabilize the variance of a measure, and it often provides the best approximation of the normal distribution (Bland and Altman 1996). However, another, less often reported, advantage of the log transformation is that the back transformation of the differences of the log-transformed data is a *ratio* (Bland and Altman 1996). For example, if we had a two samples (x & y) with an geometric mean[5] or 7 and 10.5, x and y respectively in the code below, we could represent the differences as ratio of y:x where y is 1.5 times greater than x.

```
x = 7; y = 10.5
log(y) - log(x)
```

```
## [1] 0.4054651
```

```
log(y/x)
```

```
## [1] 0.4054651
```

```
exp(log(y) - log(x))
```

```
## [1] 1.5
```

```
y/x
```

```
## [1] 1.5
```

The log transformation thereby acts as a tool help tame data into conforming to the normality assumption, and makes the interpretation fairly simple. In addition, some regulatory agencies, such as the United States Food and Drug Administration (FDA) (Food and Drug Administration 2014), specifically require bioequivalence studies to report the geometric means and make statistical comparisons on the log transformed data (He et al. 2022). These bioequivalence studies are often used to compare the maximal concentration and the area-under-the-curve (AUC) of a specific pharmaceutical to a new drug (often a generic version of the other drug). In my personal experience as a physiologist, it is not uncommon that biological/physiological phenomenon present with longer right-tailed distributions, and are often adequately normalized with a natural log transformation. The additional advantage is the how equivalence bounds can, almost, be universally applied when making comparisons on the log scale. The FDA considers to drugs to be bioequivalent when the maximal concentration and AUC differences between drugs are less than 1.25. To put it another way, ratio between two means must be between 1.25 and 0.8 (i.e., 1/1.25) (Food and Drug Administration 2014).

Therefore, I have implemented two functions to allow for the comparison of data that is believed to be left skewed (long right tail), and is on a ratio scale[6]. The first function is a parametric t-test on the log transformed scale while the second function

[5] The mean of log-transformed data is the *geometric* not *arithmetic* mean. I highly recommend reading Bland and Altman (1996) and Caldwell and Cheuvront (2019) for more details

[6] Ratio scale means the outcome is measured on a numerical scale that has equal distances between adjacent values and true zero.

is a bootstrapped base test which is more robust than parametric version (He et al. 2022).

3.3.1. Example of Log TOST

The `log_TOST` function is almost exactly the same as the `t_TOST` function. First, the primary differences is that it only accepts paired and two-sample comparisons. One-sample tests are not support (i.e., there is no ratio to calculate). Second, standardized mean differences are not calculated, but a ratio of means is instead reported (Lajeunesse 2015)[7]. Third, the default equivalence bounds are set to the FDA standards (i.e., `eqb = 1.25`), but can be changed by the user[8].

So, as an example we can use the `mtcars` data to compare the type of transmission (`am`) effects on the gas mileage (`mpg`). We can see from the data below there are significant, non-equivalent, differences in mpg between transmission types.

```
log_TOST(mpg ~ am, data = mtcars)
```

```
##
## Log-transformed Welch Two Sample t-test
##
## The equivalence test was non-significant, t(23.96) = -1.363, p = 9.07e-01
## The null hypothesis test was significant, t(23.96) = -3.826, p = 8.19e-04
## NHST: reject null significance hypothesis that the effect is equal to one
## TOST: don't reject null equivalence hypothesis
##
## TOST Results
##                 t    df p.value
## t-test     -3.826 23.96 < 0.001
## TOST Lower -1.363 23.96   0.907
## TOST Upper -6.288 23.96 < 0.001
##
## Effect Sizes
##                   Estimate      SE               C.I. Conf. Level
## log(Means Ratio)  -0.3466 0.09061 [-0.5017, -0.1916]         0.9
## Means Ratio        0.7071      NA   [0.6055, 0.8256]         0.9
```

Please note, that non-ratio data where the value of outcome variable is less than zero will lead to the function failing. For example, if you use the `sleep` data, you will notice that the outcome variable can be negative (hours of "extra" sleep).

```
log_TOST(extra ~ group, data = sleep)
```

```
## Error in log_TOST.default(x = c(0.7, -1.6, -0.2, -1.2, -0.1, 3.4, 3.7, : Negative val
```

[7] Also, referred to as a "response ratio" in ecology. Like an SMD, the response ratio can be utilized in meta-analysis.

[8] Only one value needs to be supplied to eqb; the reciprocal value of eqb is take as the other equivalence bound. For example, if `eqb = 0.85` then the upper equivalence bound is 1/0.85 (~1.333)

3.3.2. Example of Bootstrap Log TOST

The bootstrap version of `log_TOST`, `boot_log_TOST`, uses the same bootstrapping method detailed above (`boot_t_TOST`), but it uses the log-transformed values and produces the ratio of means as the effect size.

```
boot_log_TOST(mpg ~ am, data = mtcars)
```

```
##
## Bootstrapped Log Welch Two Sample t-test
##
## The equivalence test was non-significant, t(23.96) = -1.363, p = 9.55e-01
## The null hypothesis test was significant, t(23.96) = -3.826, p = 0e+00
## NHST: reject null significance hypothesis that the effect is equal to 1
## TOST: don't reject null equivalence hypothesis
##
## TOST Results
##                 t    df p.value
## t-test     -3.826 23.96 < 0.001
## TOST Lower -1.363 23.96   0.955
## TOST Upper -6.288 23.96 < 0.001
##
## Effect Sizes
##                   Estimate      SE               C.I. Conf. Level
## log(Means Ratio)  -0.3466 0.08546 [-0.4885, -0.2105]         0.9
## Means Ratio        0.7071 0.06060   [0.6136, 0.8101]         0.9
## Note: percentile bootstrap method utilized.
```

4. Equivalence Testing with ANOVAs

Many researchers utilize ANOVA as an omnibus test for the absence/presence of effects before inspecting multiple pairwise comparisons. This is very useful when implementing factorial designs where multiple experimental factors are tested and/or manipulated. As Campbell and Lakens (2021) suggest, the lack of a significant result at the ANOVA-level does not necessarily indicate that a factor or interaction of factors have no effect. However, Campbell and Lakens (2021) only suggest an equivalence test for one-way ANOVAs and therefore exclude multi-factor or factorial ANOVAs. Therefore, I have extended the work of Campbell and Lakens (2021) to include functions that allow for equivalence testing of the partial η^2 (eta-squared) effect size from ANOVAs.

4.1. *F-test Calculations*

Statistical equivalence testing[9] for F-tests are special use case of the cumulative distribution function of the non-central F distribution. As Campbell and Lakens (2021) states, these type of questions answer the question: "Can we reject the hypothesis that the total proportion of variance in outcome Y attributable to X is greater than or equal to the equivalence bound Δ?"

4.1.1. Hypothesis Tests

$$H_0 = 1 > \eta_p^2 \geq \Delta$$

$$H_1 = 0 \geq \eta_p^2 < \Delta$$

In TOSTER, I have gone a tad farther than Campbell and Lakens (2021), and have included a calcuation for a generalization of the non-centrality parameter that allows the equivalence test for F-tests to be applied to variety of designs.

Campbell and Lakens (2021) calculate the p-value as:

$$p = p_f(F; J-1, N-J, \frac{N \cdot \Delta}{1-\Delta})$$

The non-centrality parameter (ncp $= \lambda$) can be calculated with the equivalence bound and the degrees of freedom:

$$\lambda_{eq} = \frac{\Delta}{1-\Delta} \cdot (df_1 + df_2 + 1)$$

The p-value for the equivalence test (p_{eq}) could then be calculated from traditional ANOVA results and the distribution function:

[9] Also called "omnibus non-inferiority testing" by Campbell and Lakens (2021)

$$p_{eq} = p_f(F; df_1, df_2, \lambda_{eq})$$

4.2. *Example of Equivalence ANOVA Test*

Using the `InsectSprays` data set in R and the base R `aov` function we can demonstrate how this omnibus equivalence testing can be applied with TOSTER. From the initial analysis we an see a clear "significant" effect (the p-value listed is zero but it just very small) of the factor spray. However, we *may* be interested in testing if the effect is practically equivalent. I will arbitrarily set the equivalence bound to a partial eta-squared of 0.35 ($H_0 : \eta_p^2 > 0.35$)

```
data("InsectSprays")
aovtest = aov(count ~ spray, data = InsectSprays)
aovtest
```

```
## Call:
##    aov(formula = count ~ spray, data = InsectSprays)
##
## Terms:
##                     spray Residuals
## Sum of Squares  2668.833  1015.167
## Deg. of Freedom        5        66
##
## Residual standard error: 3.921902
## Estimated effects may be unbalanced
```

We can then use the information in the table above to perform an equivalence test using the `equ_ftest` function. This function returns an object of the S3 class `htest` and the output will look very familiar to the the t-test. The main difference is the estimates, and confidence interval, are for partial η_p^2.

```
equ_ftest(Fstat = 34.70228,
          df1 = 5,
          df2 = 66,
          eqb = 0.35)
```

```
##
##  Equivalence Test from F-test
##
## data:  Summary Statistics
## F = 34.702, df1 = 5, df2 = 66, p-value = 1
## 95 percent confidence interval:
##  0.5806263 0.7804439
## sample estimates:
## [1] 0.724439
```

Based on the results above we would conclude there is a significant effect of "spray" and the differences due to spray are *not* statistically equivalent. In essence, we reject

the traditional null hypothesis of "no effect" but accept the null hypothesis of the equivalence test.

The `equ_ftest` is very useful because all you need is very basic summary statistics. However, if you are doing all your analyses in R then you can use the `equ_anova` function. This function accepts objects produced from `stats::aov`, `car::Anova` and `afex::aov_car` (or any ANOVA from derived from `afex`).

```
equ_anova(aovtest,
          eqb = 0.35)
```

```
##        effect df1 df2  F.value       p.null      pes eqbound     p.equ
## 1 spray         5  66 34.70228 3.182584e-17 0.724439    0.35 0.9999965
```

5. Equivalence Between Replication Studies

During the development of the TOSTER update, I was helping advise a team of researchers on a massive replication project for sport and exercise science (Murphy et al. 2022). How to determine whether a direct[10] replication was equivalent to the original study was common, and contentious, topic of conversation among the team. Inspired by these discussions, I created 2 functions that would utilize the basic principles of SMDs[11] to test for differences between two studies.

Overall, the concept is simple: if we have an estimates of SMDs from two studies we can use large-sample approximation to compute the sampling variances to estimate the degree to which the two studies differ from one another. The users of TOSTER then have the option to test whether the two SMDs significantly differ, or use TOST to estimate if they are practically equivalent. Additionally, there are two options for comparing SMDs: using the summary statistics or using bootstrapping (assuming original data is available).

5.1. *Example using Summary Statistics*

In this example, let us imagine an "original" study that reports an effect of Cohen's dz = 0.95 in a paired samples design with 25 subjects. However, a replication doubled the sample size, found a non-significant effect at an SMD of 0.2. Are these two studies compatible? Or, to put it another way, should the replication be considered a "failure" to replicate the oringal study?

We can use the `compare_smd` function to at least measure how often we would expect a discrepancy between the original and replication study if the same underlying effect was being measured (also assuming no publication bias).

We can see from the results below that, if the null hypothesis were true, we would only expect to see a discrepancy in SMDs between studies at least this large ~1% of the time.

```
compare_smd(smd1 = 0.95,
            n1 = 25,
            smd2 = 0.23,
            n2 = 50,
            paired = TRUE)
```

```
##
##  Difference in Cohen's dz (paired)
##
## data:  Summary Statistics
## z = 2.5685, p-value = 0.01021
## alternative hypothesis: true difference in SMDs is not equal to 0
## sample estimates:
## difference in SMDs
##               0.72
```

[10] Defined as being a as-close-as possible replication to the original study. In contrast to "conceptual" replications.

[11] The textbook by Borenstein et al. (2021) and the some of the works of Wolfgang Vietchbauer were a large source of information for developing these functions.

Let us also imagine a scenario where a replication team considers a replication successful if the SMDs are within 0.25 units of each other. We can set the `TOST` argument to TRUE, and then set the equivalence bound using `null` argument.

```
compare_smd(smd1 = 0.95, n1 = 25, smd2 = 0.23,n2 = 50,
            paired = TRUE, TOST = TRUE, null = .25)
```

```
##
##  Difference in Cohen's dz (paired)
##
## data:  Summary Statistics
## z = 1.6767, p-value = 0.9532
## alternative hypothesis: true difference in SMDs is less than 0.25
## sample estimates:
## difference in SMDs
##               0.72
```

Based on the imaginary studies we outlined above, we would not reject the null equivalence hypothesis, but reject the null significance hypothesis. Therefore, we would could conclude that there are significant differences between the studies that are not practically equivalent.

5.2. *Example using Bootstrapping*

The above results are only based on an approximating the differences between the SMDs. If the raw data is available, then the optimal solution is the bootstrap. This can be accomplished with the `boot_compare_smd` function. The only drawback to this function is that TOST is currently not avaiable, and users would instead have to run 2 one-sided tests manually using the `null` and `alternative` arguments.

For this example, we will simulate some data. As an alternative approach to TOST, we can just set the `alpha` to 0.1, and then check to see if the confidence interval is within the preset equivalence bounds.

```
set.seed(4522)
boot_test = boot_compare_smd(x1 = rnorm(25,.95), x2 = rnorm(50),
                             paired = TRUE, alpha = .1)
boot_test
```

```
##
##  Bootstrapped Differences in SMDs (paired)
##
## data:  Bootstrapped
## z (observed) = 2.887, p-value = 0.006003
## alternative hypothesis: true difference in SMDs is not equal to 0
## 90 percent confidence interval:
##  0.4070761 1.3508435
## sample estimates:
## difference in SMDs
##          0.8058872
```

6. Conclusions

- This can be useful.
- This package is not exhaustive but is good for simple analyses and teaching

7. Additional Information

All analyses/code in this manuscript are from TOSTER v0.6.0:

```
# Install the exact release with this code
devtools::install_github("Lakens/TOSTER@v0.6.0")
```


Acknowledgement(s)

I'd would like to thank everyone from the Lakens' laboratory group for their input and suggestions.

Disclosure statement

The author of this manuscript is the author of the TOSTER package. Citations of this manuscript will benefit their citation count.

Funding

No funding was provided for this work.

Notes on contributor(s)

Daniel Lakens provided a review of many of the materials that have been incorporated into the update of TOSTER, and was the original author of this package.

Nomenclature/Notation

- ANOVA: Analysis of Variance
- Bootstrapping: the use of random sampling with replacement to estimate statistics
- FDA: Food and Drug Administration (United States of America)
- MET: Minimal Effects Test
- ncp: non-centrality parameter
- SMD: Standardized Mean Difference (e.g., Cohen's d)
- TOST: Two-One Sided Tests
- WMW: Wilcoxon-Mann-Whitney

Notes

The R package is also (partially) implemented in jamovi as the TOSTER module.

References

Altman, Douglas G, and J Martin Bland. 1995. "Statistics notes: Absence of evidence is not evidence of absence." *BMJ* 311 (7003): 485. https://doi.org/10.1136/bmj.311.7003.485.

Bland, J Martin, and Douglas G Altman. 1996. "Statistics notes: the use of transformation when comparing two means." *BMJ* 312 (7039): 1153. https://doi.org/10.1136/bmj.312.7039.1153.

Borenstein, Michael, Larry V Hedges, Julian PT Higgins, and Hannah R Rothstein. 2021. *Introduction to meta-analysis*. John Wiley & Sons.

Caldwell, Aaron R, and Samuel N Cheuvront. 2019. "Basic statistical considerations for physiology: The journal Temperature toolbox." *Temperature* 6 (3): 181–210. https://doi.org/10.1080/23328940.2019.1624131.

Campbell, Harlan, and Daniël Lakens. 2021. "Can we disregard the whole model? Omnibus non-inferiority testing for R2 in multi-variable linear regression and in ANOVA." *British Journal of Mathematical and Statistical Psychology* 74 (1): e12201. https://bpspsychub.onlinelibrary.wiley.com/doi/abs/10.1111/bmsp.12201.

Divine, George W, H James Norton, Anna E Barón, and Elizabeth Juarez-Colunga. 2018. "The Wilcoxon–Mann–Whitney procedure fails as a test of medians." *The American Statistician* 72 (3): 278–286. https://doi.org/10.1080/00031305.2017.1305291.

Efron, Bradley, and Robert J. Tibshirani. 1993. *An Introduction to the Bootstrap*. Monographs on Statistics and Applied Probability 57. Boca Raton, Florida, USA: Chapman & Hall/CRC.

Food and Drug Administration. 2014. *Bioavailability and Bioequivalence Studies Submitted in NDAs or INDs — General Considerations*. Vol. FDA-2014-D-0204. Center for Drug Evaluation and Research. https://www.fda.gov/regulatory-information/search-fda-guidance-documents/bioavailability-and-bioequivalence-studies-submitted-ndas-or-in.

He, Y, Y Deng, C You, and X H Zhou. 2022. "Equivalence tests for ratio of means in bioequivalence studies under crossover designs." *Statistical Methods in Medical Research* 09622802221093721. https://doi.org/10.1177/09622802221093721.

Hedges, Larry V. 1981. "Distribution theory for Glass's estimator of effect size and related estimators." *journal of Educational Statistics* 6 (2): 107–128. https://doi.org/10.3102/10769986006002107.

Kerby, Dave S. 2014. "The Simple Difference Formula: An Approach to Teaching Nonparametric Correlation." *Comprehensive Psychology* 3: 11.IT.3.1. http://dx.doi.org/10.2466/11.it.3.1.

Kornbrot, Diana Eugenie. 1990. "The rank difference test: A new and meaningful alternative to the Wilcoxon signed ranks test for ordinal data." *British Journal of Mathematical and Statistical Psychology* 43 (2): 241–264. https://doi.org/10.1111/j.2044-8317.1990.tb00939.x.

Lajeunesse, Marc J. 2015. "Bias and correction for the log response ratio in ecological meta-analysis." *Ecology* 96 (8): 2056–2063. https://doi.org/10.1890/14-2402.1.

Lakens, Daniël. 2017. "Equivalence tests: A practical primer for t-tests, correlations, and meta-analyses." *Social Psychological and Personality Science* 1: 1–8. https://doi.org/10.1177/1948550617697177.

Lakens, Daniël, Neil McLatchie, Peder M Isager, Anne M Scheel, and Zoltan Dienes. 2020. "Improving inferences about null effects with Bayes factors and equivalence tests." *The Journals of Gerontology: Series B* 75 (1): 45–57. https://doi.org/10.1093/geronb/gby065.

Lakens, Daniël, Anne M Scheel, and Peder M Isager. 2018. "Equivalence testing for psychological research: A tutorial." *Advances in Methods and Practices in Psychological Science* 1 (2): 259–269. https://doi.org/10.1177/2515245918770963.

Mazzolari, Raffaele, Simone Porcelli, David J Bishop, and Daniël Lakens. 2022. "Myths and methodologies: The use of equivalence and non-inferiority tests for interventional studies in exercise physiology and sport science." *Experimental Physiology* 107 (3): 201–212. https:

//doi.org/10.1113/EP090171.

Murphy, Jennifer, Cristian Mesquida, Aaron R Caldwell, Brian D Earp, and Joe P Warne. 2022. "Proposal of a Selection Protocol for Replication of Studies in Sports and Exercise Science." *Sports Medicine* 1–11. https://doi.org/10.1007/s40279-022-01749-1.

O'Brien, Ralph G, and John Castelloe. 2006. "Exploiting the link between the Wilcoxon-Mann-Whitney test and a simple odds statistic." 209–31. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.590.1204&rep=rep1&type=pdf.

Schuirmann, Donald J. 1987. "A comparison of the two one-sided tests procedure and the power approach for assessing the equivalence of average bioavailability." *Journal of pharmacokinetics and biopharmaceutics* 15 (6): 657–680. https://doi.org/10.1007/BF01068419.