Conversion of Common Test Statistics to *r* and *d* Values

Statistic		*r*-value	*d*-value
1.	t	$\sqrt{\frac{t^2}{(t^2 + df)}}$	$\frac{2t}{\sqrt{df}}$
2.	z	$\sqrt{\frac{z^2}{z^2 + N}}$	$\frac{2z}{\sqrt{N}}$
3.	$F\ df_n = 1$	$\sqrt{\frac{F}{F + df_d}}$	$2\sqrt{\frac{F}{df_d}}$
4.	$F\ df_n > 1$	$\sqrt{\frac{df_n F}{df_n F + df_d}}$	$2\sqrt{\frac{df_n F}{df_d}}$
5.	$\chi^2\ df = 1$	$\sqrt{\frac{\chi^2}{N}}$	$2\sqrt{\frac{\chi^2}{N - \chi^2}}$
6.	$\chi^2\ df > 1$	$\sqrt{\frac{\chi^2}{\chi^2 + N}}$	$2\sqrt{\frac{\chi^2}{N}}$
7.	r	r	$\sqrt{\frac{4r^2}{1 - r^2}}$
8.	d	$\sqrt{\frac{d^2}{4 + d^2}}$	d

Note. df_n = degrees of freeedom for the numerator, df_d = degrees of freedom for the denominator. Tables taken after Friedman (1982) and Wolf (1986).

Cohen suggested computing: $d = \frac{(\bar{Y}_1 - \bar{Y}_2)}{\sqrt{(s_1^2 + s_2^2)/2}}$.

Hedges and Olkin (1985) suggested an adjusted *d*, $\tilde{d} = \frac{(\bar{Y}_1 - \bar{Y}_2)}{\sqrt{(s_1^2 + s_2^2)/2}}\left[1 - \left[\frac{3}{4(n_1 + n_2) - 9}\right]\right]$ and

Hedges' $g = \frac{(\bar{Y}_1 - \bar{Y}_2)}{\sqrt{((n_1 - 1)s_1^2 + (n_2 - 1)s_2^2)/((n_1 + n_2 - 2))}}\left[1 - \left[\frac{3}{4(n_1 + n_2) - 9}\right]\right]$

Common Critical Values from the Normal Distribution
for Quick Approximate Power Analysis

Power	Distance	$\alpha = 0.05$ 1-tailed (1.645)	$\alpha = 0.05$ 2-tailed (1.960)	$\alpha = 0.01$ 1-tailed (2.326)	$\alpha = 0.01$ 2-tailed (2.576)
0.70	-0.525	**2.170**	**2.485**	**2.846**	**3.101**
0.80	-0.842	**2.487**	**2.802**	**3.168**	**3.418**
0.90	-1.282	**2.927**	**3.242**	**3.608**	**3.858**

For a 2-group design, approximate per group sample size (n_j) for a given α and level of Statistical Power (**1-β**) for the can be solved as:

$n_j \geq \frac{2z_{cv}^2}{d^2}$, where z_{cv}^2 is the critical value from the Table above, d is a standardized mean difference, $d = \frac{(\bar{Y}_1 - \bar{Y}_2)}{s}$, and s is an assumed standard deviation. As pointed out above, various metrics have been proposed. In general, the use of Cohen's *d* the adjusted *d*, or Hedges' *g* will lead to approximately the same result.

For example, suppose a study reports the control group had a mean of $\bar{Y}_C$=10, the treatment group had a mean of $\bar{Y}_T$=12 and the pooled standard deviation was s = 1.5.
Then the standardized mean difference would be: d = (12.7-11.8)/1.5 = 0.6.
For a future study to have **70% Power (1-β = 0.70)** for a 2-tailed test at **α = 0.05**
The approximate necessary per group sample size would be:

$$n_j \geq \frac{2(2.485^2)}{0.6^2} \geq \frac{2(6.175225)}{0.36} \geq 34.3 \approx 35.$$

For a future study to have **80% Power (1-β = 0.80)** for a 2-tailed test at **α = 0.01**

The approximate necessary per group sample size would be:

$$n_j \geq \frac{2(3.418^2)}{0.6^2} \geq \frac{2(11.682724)}{0.36} \geq 64.9 \approx 65.$$

Reversing this process, if a researcher knew that he could only obtain 100 total subjects (n_j = 50 per group), then we could solve for an approximate minimum effect size (d):

$$d \geq \frac{z_{cv}}{\sqrt{\frac{n_j}{2}}}$$

Thus, if the research desired **80% Power (1-β = 0.80)** for a 2-tailed test at **α = 0.05**

$d \geq \frac{2.802}{\sqrt{\frac{50}{2}}} \geq \frac{2.802}{5} \geq 0.5604$ would be the approximate necessary effect size.

To double check this enter the effect size of d = 0.5604 the critical value for **80% Power (1-β = 0.80)** for a 2-tailed test at **α = 0.05** into

$$n_j \geq \frac{2z_{cv}^2}{d^2} \geq \frac{2(2.802^2)}{0.5604^2} \geq \frac{15.702408}{0.31404816} \geq 50$$