# Summary of Effect Sizes and their Links to Inferential Statistics

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- 1. Definitions of effect sizes
  - 1.1. Effect sizes expressing the degree of association between two variables (r)

  - 1.2. Effect sizes expressing the degree of difference between means (d, g) 1.3. Effect sizes expressing the "proportion of variance explained" ( $R^2$ ,  $\eta^2$ ,  $\omega^{2}$ )
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- 2. Transforming between effect sizes
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Much of this is based on :

- Rosenthal, R. (1994). Parametric measures of effect size. In H. Cooper & L. V. Hedges (Eds.), The handbook of research synthesis (pp. 231-244). New York: Russell Sage Foundation.
- Rosenthal, R. Rosnow, R. L., & Rubin, D. B. (2000) Contrasts and effect sizes in behavioral research: A correlational approach. Cambridge, UK: Cambridge University Press.

Please feel free to contact me if any of these formulae seem incorrect – it is possible that typographical errors may have been made.

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#### 1. EFFECT SIZES: DEFINITIONS

#### **<u>1.1 Degree of association between two variables (Correlational Effect Sizes)</u>**

$$r = \Phi = r_{pb} = \frac{\sum Z_x Z_y}{n} = \frac{\sum \left(\frac{X - \overline{X}}{\sqrt{\frac{\sum (X - \overline{X})^2}{n}}}\right) \left(\frac{Y - \overline{Y}}{\sqrt{\frac{\sum (Y - \overline{Y})^2}{n}}}\right)}{n} = \frac{\frac{\sum (X - \overline{X})(Y - \overline{Y})}{n}}{\sigma_x \sigma_y} = \frac{\sigma_{xy}}{\sigma_x \sigma_y} = \frac{s_{xy}}{s_x s_y}$$

NOTE: Some of these formulas use n in the denominator of the correlation, but they are sometimes written with n-1 rather than n in the denominators. This difference does not matter as long as either n or n-1 is used in all parts of the equation (ie, in the standard deviations, z-scores, covariance, etc)

When r is a point-biserial correlation  $(r_{pb})$ , it is based on a dichotomous grouping variable (X) and a continuous variable (Y). In this case, the equation can also be written as:

$$r = \frac{\sqrt{p_1 p_2} \left(\overline{Y}_1 - \overline{Y}_2\right)}{\sigma_Y}$$

where p1 and p2 are the proportions of the total sample in each group,  $(\overline{Y_1} - \overline{Y_2})$  is the difference between the groups'

means on the continuous variable (Y), and  $\sigma_{Y}$  is the standard deviation of variable Y. Note that this is Equation 5 in McGrath and Meyer (2006), and note that the direction of the correlation depends on which group is considered group 1 and which is considered group 2.

McGrath, R. E., & Meyer, G. J. (2006). When effect sizes disagree: The case of r and d. Psychological Methods, 11, 386-401.

Z transformation of a correlation

$$z_r = r' = \frac{1}{2} \log_e \left[ \frac{1+r}{1-r} \right] = \frac{1}{2} \left[ \log_e (1+r) - \log_e (1-r) \right]$$

Where log<sub>e</sub> is the natural log function (LN on some calculators)

To transform back from  $z_r(r')$  metric to r metric

$$r = \frac{e^{2Z_r} - 1}{e^{2Z_r} + 1}$$

Where e is the exponent function ( $e^{X}$  on some calculators)

#### Effect size for the difference between correlations

Cohen's  $q = Z_{r1} - Z_{r2}$ 

## **1.2 Degree of difference between two means (Effect sizes a la d)**

1.2.1 . For comparing means from two groups:

Cohen's d = 
$$\frac{\overline{X}_1 - \overline{X}_2}{\sigma_{\text{pooled}}}$$

Hedges's 
$$g = \frac{\overline{X}_1 - \overline{X}_2}{s_{pooled}}$$

Glass's 
$$\Delta = \frac{\overline{X}_1 - \overline{X}_2}{s_{\text{control group}}}$$

Where

$$\sigma_{\text{pooled}} = \sqrt{\frac{(n_1)\sigma_1^2 + (n_2)\sigma_2^2}{n_1 + n_2}} \quad \text{and} \quad s_{\text{pooled}} = \sqrt{\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}}$$
  
and  $\sigma_{\text{pooled}} = s_{\text{pooled}} \sqrt{\frac{n_1 + n_2 - 2}{n_1 + n_2}} = s_{\text{pooled}} \sqrt{\frac{N - 2}{N}}$   
and  $s_{\text{pooled}} = \frac{\sigma_{\text{pooled}}}{\sqrt{\frac{n_1 + n_2 - 2}{n_1 + n_2}}} = \frac{\sigma_{\text{pooled}}}{\sqrt{\frac{N - 2}{N}}}$ 

You may also see  $\sigma_{\text{pooled}}$  referred to as  $\sigma_{\text{within}}$ , and  $s_{\text{pooled}}$  referred to as  $s_{\text{within}}$  or as  $\sqrt{MS_{\text{within}}}$ 

1.2.2 The logic of d and g can be applied when comparing one mean to a population mean (e.g., one sample t-test), such that:

$$d = \frac{\overline{X} - \mu}{\sigma_X}$$

$$g = \frac{X - \mu}{s_X}$$

where  $\mu$  is the null hypothesis population mean

1.2.3 The logic of d and g can be applied when comparing two correlated means (e.g., repeated measures t-test, paired samples t-test)

$$d = \frac{\overline{D}}{\sigma_D}$$

$$g = \frac{\overline{D}}{s_{D}}$$

where  $\overline{D}$  is the mean difference score and  $\sigma_D$  and  $s_D$  are standard deviations of the difference scores

# 1.3 "Variance accounted for" $R^2$ , Eta squared ( $\eta^2$ ), and omega squared ( $\omega^2$ )

$$R^{2} = \eta^{2} = \frac{SS_{EXPLAINED}}{SS_{TOTAL}} = \frac{SS_{BETWEEN}}{SS_{TOTAL}}$$

For a specific effect (ie, in a study with multiple IVs/predictors)  $R^2 = \eta^2 = R_{EFFECT}^2 = \eta_{EFFECT}^2 = \frac{SS_{EFFECT}}{SS_{TOTAL}}$ 

Omega squared for an effect =  $\omega_{EFFECT}^2 = \frac{\sigma_{EFFECT}^2}{\sigma_{TOTAL}^2} = \frac{SS_{EFFECT} - df_{EFFECT}MS_{ERROR}}{SS_{TOTAL} + MS_{ERROR}}$ 

# **1.4 Effect sizes for proportions**

Cohen's g = p - .50where *p* estimates a population proportion

 $d' = p_1 - p_2$ where  $p_1$  and  $p_2$  are estimates of the population proportions

Cohen's  $h = \arcsin p_1 - \arcsin p_2$ 

Pr obit d' =  $Z_{p_1} - Z_{p_2}$ where  $Z_{p_1}$  and  $Z_{p_2}$  are standard normal deviate transformed estimates of population proportions

Logit d' =  $\log_e \left[ \frac{p_1}{1-p_1} \right] - \log_e \left[ \frac{p_2}{1-p_2} \right]$ 

#### 2. TRANSFORMING BETWEEN EFFECT SIZES

# 2.1 Computing r

2.1.1 Computing r from Cohen's d

For one group and for two correlated means (ie repeated measures or paired samples)

$$r = \sqrt{\frac{d^2}{d^2 + 1}} = \frac{d}{\sqrt{d^2 + 1}}$$

For two independent groups

$$r = \sqrt{\frac{d^2}{d^2 + \frac{1}{p_1 p_2}}}$$

Where p<sub>1</sub> is the proportion of participants who are in Group 1 and p<sub>2</sub> is the proportion in Group 2

Note, for equal sample sizes (p<sub>1</sub> = p<sub>2</sub> = .50), this simplifies to:  $r = \sqrt{\frac{d^2}{d^2 + 4}}$ 

# 2.1.2. Computing r from Hedge's g

For one group and for two correlated means (ie repeated measures or paired samples)

$$r = \sqrt{\frac{g^2}{g^2 + \frac{df}{N}}} = \sqrt{\frac{g^2}{g^2 + \frac{N-1}{N}}}$$

For two independent groups

$$r = \sqrt{\frac{g^2 n_1 n_2}{g^2 n_1 n_2 + (n_1 + n_2)df}} = \sqrt{\frac{g^2}{g^2 + \frac{df}{Np_1 p_2}}} = \sqrt{\frac{g^2}{g^2 + \frac{N - 2}{Np_1 p_2}}}$$

Where p<sub>1</sub> is the proportion of participants who are in Group 1 and p<sub>2</sub> is the proportion in Group 2

Note, for equal sample sizes (p<sub>1</sub> = p<sub>2</sub> = .50), this simplifies to: 
$$r = \sqrt{\frac{g^2}{g^2 + 4\left(\frac{N-2}{N}\right)}}$$

## 2.2 Computing d

#### 2.2.1 Computing d from r

For one group and for two correlated means (ie repeated measures or paired samples)

$$d = \frac{r}{\sqrt{1 - r^2}}$$

For two independent groups

$$d = \frac{r}{\sqrt{p_1 p_2 \left(l - r^2\right)}}$$

Where  $p_1$  is the proportion of participants who are in Group 1 and  $p_2$  is the proportion in Group 2

Note, for equal sample sizes (p<sub>1</sub> = p<sub>2</sub> = .50), this simplifies to:  $d = \frac{2r}{\sqrt{1-r^2}}$ 

# 2.2.2. Computing d from Hedge's g

For one group and for two correlated means (ie repeated measures or paired samples)

$$d = g\sqrt{\frac{N}{df}} = g\sqrt{\frac{N}{N-1}}$$

For two independent groups (regardless of the relative sample sizes)

$$d = g \sqrt{\frac{N}{df}} = g \sqrt{\frac{N}{N-2}}$$

# 2.3 Computing g

#### 2.3.1 Computing g from r

For one group and for two correlated means (ie repeated measures or paired samples)

$$g = \frac{r}{\sqrt{1 - r^2}} \sqrt{\frac{df}{N}} = \frac{r}{\sqrt{1 - r^2}} \sqrt{\frac{N - 1}{N}}$$

For two independent groups

$$g = \frac{r}{\sqrt{p_1 p_2 \left(l - r^2\right)}} \sqrt{\frac{df}{N}} = \frac{r}{\sqrt{p_1 p_2 \left(l - r^2\right)}} \sqrt{\frac{N - 2}{N}}$$

Where p<sub>1</sub> is the proportion of participants who are in Group 1 and p<sub>2</sub> is the proportion in Group 2

Note, for equal sample sizes (p<sub>1</sub> = p<sub>2</sub> = .50), this simplifies to:  $g = \frac{2r}{\sqrt{1-r^2}} \sqrt{\frac{df}{N}} = \frac{2r}{\sqrt{1-r^2}} \sqrt{\frac{N-2}{N}}$ 

# 2.3.2 Computing g from Cohen's d

For one group and for two correlated means (ie repeated measures or paired samples)

$$g = d\sqrt{\frac{df}{N}} = d\sqrt{\frac{N-1}{N}}$$

For two independent groups (regardless of the relative sample sizes)

$$g=d\sqrt{\frac{df}{N}}=d\sqrt{\frac{N-2}{N}}$$

# **2.4** Transforming between eta squared ( $\eta^2$ ) and omega squared ( $\omega^2$ )

eta<sup>2</sup> for an effect = 
$$\eta^2 = \frac{\left(df_{effect} + \frac{nk\omega^2}{1-\omega^2}\right)\left(\frac{1}{df_{error}}\right)}{\left(df_{effect} + \frac{nk\omega^2}{1-\omega^2}\right)\left(\frac{1}{df_{error}}\right) + 1}$$

Where n is the number of individuals per group, and k is the number of groups for the effect

omega2 for an effect = 
$$\omega^2 = \frac{\frac{df_{error}\eta^2}{1-\eta^2} - df_{effect}}{\left(\frac{df_{error}\eta^2}{1-\eta^2} - df_{effect}\right) + nk}$$

#### 3. COMPUTING SIGNIFICANCE TESTS FROM EFFECT SIZES

Recall, Inferential test statistic = Effect size X Size of Study

#### 3.1 For a 2 x 2 Contingency table

$$\chi^2_{(1)} = Z^2 = r^2 N$$

# 3.2 For a t-test

3.2.1 T from r

This is appropriate for any kind of t-test:

$$t = \frac{r}{\sqrt{1 - r^2}} \sqrt{df}$$

3.2.2 T from Cohen's d

3.2.2.1 For a One-sample t-test or correlated means t-test

$$t = d\sqrt{df} = d\sqrt{N-1}$$
 where  $d = \frac{\overline{X} - \mu}{\sigma_X}$  or  $d = \frac{\overline{D}}{\sigma_D}$ 

3.2.2.2 For an independent groups t-test

$$t = d \left( \frac{\sqrt{n_1 n_2}}{(n_1 + n_2)} \right) \sqrt{df} = d \sqrt{p_1 p_2 df} = d \sqrt{p_1 p_2 (N - 2)}$$

Where  $p_1$  is the proportion of participants who are in Group 1 and  $p_2$  is the proportion in Group 2

Note, for equal sample sizes (p<sub>1</sub> = p<sub>2</sub> = .50), this simplifies to:  $t = d \frac{\sqrt{df}}{2} = d \frac{\sqrt{N-2}}{2}$ 

3.2.3 T from Hedge's g

3.2.3.1 For a One-sample t-test or correlated means t-test

$$t = g\sqrt{N}$$
 where  $g = \frac{\overline{X} - \mu}{s_X}$  or  $g = \frac{\overline{D}}{s_D}$ 

3.2.3.2 For an independent groups t-test

$$t = g\left(\sqrt{\frac{n_1n_2}{n_1 + n_2}}\right) = g\sqrt{p_1p_2N}$$

Where  $p_1$  is the proportion of participants who are in Group 1 and  $p_2$  is the proportion in Group 2

Note, for equal sample sizes  $(n_1 = n_2 = n \text{ and } p_1 = p_2 = .50)$ , this simplifies to:  $t = g \frac{\sqrt{N}}{2} = g \sqrt{\frac{n}{2}}$ 

# 3.3 For an ANOVA (F test)

# 3.3.1 For an ANOVA with $df_{NUMERATOR} = 1$ (two independent groups)

$$F = \frac{r^2}{1 - r^2} (df_{error})$$

$$F = d^{2} (df_{error} p_{1} p_{2})$$
  
(for equal n study,  $F = d^{2} \left( \frac{df_{error}}{4} \right)$ 

$$F = g^{2}\left(\frac{n_{1}n_{2}}{n_{1}+n_{2}}\right) = g^{2}\left(nkp_{1}p_{2}\right) = g^{2}\left(Np_{1}p_{2}\right) \text{ for a oneway ANOVA}$$
  
(for equal n study,  $F = g^{2}\left(\frac{nk}{4}\right) = g^{2}\left(\frac{N}{4}\right)$  for a oneway ANOVA

$$F = \frac{\text{eta}^2}{1 - \text{eta}^2} (\text{df}_{\text{error}})$$
$$F = \frac{\omega^2}{1 - \omega^2} (\text{nk}) + 1 = \frac{\omega^2}{1 - \omega^2} (\text{N}) + 1 \quad \text{for a oneway ANOVA}$$

3.3.2 For an ANOVA with  $df_{NUMERATOR} > 1$  (more than two independent groups)

$$F = \frac{\text{eta}^2}{1 - \text{eta}^2} \left( \frac{\text{df}_{\text{error}}}{\text{df}_{\text{means}}} \right)$$
$$F = \frac{\omega^2}{1 - \omega^2} \left( \frac{\text{nk}}{\text{k} - 1} \right) + 1$$

# 4. COMPUTING EFFECT SIZES FROM SIGNIFICANCE TESTS

# 4.1 Computing r

4.1.1 r from a  $X^2$  test for a 2x2 contingency table

$$r = \Phi = r_{pb} = \sqrt{\frac{\chi^2(l)}{n}} = \frac{Z}{\sqrt{n}}$$

4.1.2 r from any t test (or F-test with numerator df = 1)

$$r = \sqrt{\frac{t^2}{t^2 + df}} = \sqrt{\frac{F}{F + df_{error}}}$$

# 4.2 Computing d

4.2.1 d from a one-sample t-test or correlated means t-test

$$d=\frac{t}{\sqrt{df}}=\frac{t}{\sqrt{N-1}}$$

4.2.2 d from an independent groups t-test

$$d = t \left( \frac{n_1 + n_2}{\sqrt{df} \sqrt{n_1 n_2}} \right) = \frac{t}{\sqrt{p_1 p_2 df_{error}}} = \frac{t}{\sqrt{p_1 p_2 (N - 2)}}$$

Which simplifies to  $d = \frac{2t}{\sqrt{df}}$  if the groups have equal n

4.2.3 d from an F test based on numerator df = 1

$$d = \frac{\sqrt{F}}{\sqrt{p_1 p_2 df_{error}}} = \frac{\sqrt{F}}{\sqrt{p_1 p_2 (N-2)}}$$

Which simplifies to  $d = \frac{2\sqrt{F}}{\sqrt{df}}$  if the groups have equal n

# 4.3 Computing g

4.3.1 g from a one-sample t-test or correlated means t-test

$$g = \frac{t}{\sqrt{N}}$$

4.3.2 g from an independent groups t-test

$$g = t \sqrt{\frac{n_1 + n_2}{n_1 n_2}} = \frac{t}{\sqrt{p_1 p_2 N}}$$

Which simplifies to  $g = \frac{2t}{\sqrt{N}}$  if the groups have equal n

4.3.3 g from an F test based on numerator df = 1

$$g = \frac{\sqrt{F}}{\sqrt{p_1 p_2 N}}$$

Which simplifies to  $g = \frac{2\sqrt{F}}{\sqrt{N}}$  if the groups have equal n

# **4.4 Computing** $\eta^2$ and $\omega^2$

eta<sup>2</sup> for an effect = 
$$\eta^2 = \frac{\frac{F_{effect}(df_{effect})}{df_{error}}}{\frac{F_{effect}(df_{effect})}{df_{error}} + 1} = \frac{F_{effect}(df_{effect})}{F_{effect}(df_{effect}) + df_{error}}$$

omega<sup>2</sup> for an effect = 
$$\omega^2 = \frac{(F_{effect} - 1)(df_{effect})}{(F_{effect} - 1)(df_{effect}) + nk}$$

For F tests with numerator = 1, these simplify to

eta<sup>2</sup> for an effect = 
$$\eta^2 = \frac{\frac{F_{effect}}{df_{error}}}{\frac{F_{effect}}{df_{error}} + 1} = \frac{F_{effect}}{F_{effect} + df_{error}}$$

omega<sup>2</sup> for an effect = 
$$\omega^2 = \frac{(F_{effect} - 1)}{(F_{effect} - 1) + nk}$$