Guidelines for Calculating Effect Sizes for Practice-Based Research Syntheses

Carl J. Dunst, Deborah W. Hamby, and Carol M. Trivette

This Centerscope article includes guidelines for calculating Cohen’s $d$ effect sizes for the relationship between the independent variables and outcome measure for studies included in a practice-based research synthesis. A practice-based research synthesis includes studies where variations in practice characteristics are related to variations in outcomes. Different formulas and procedures are presented for different kinds of research designs and research studies. The guidelines were developed in order to be able to calculate effect sizes from different kinds of research studies included in the same practice-based research synthesis so that the effect sizes have the same or similar interpretive meaning.

This Centerscope article includes guidelines for calculating the effect sizes for the relationship between the practice characteristics (interventions) and the outcomes in studies included in practice-based research syntheses (Dunst, Trivette, & Cutspec, 2002a, 2002b). This approach to culling research evidence generally includes a small number of studies that have examined the same or similar practice characteristics where variations in measures of adherence to the practices are related to variations in the consequences of the practices. Practice-based research syntheses often include studies using different research designs and data analysis procedures for relating variations in practice characteristics to variations in outcomes.

The primary purpose of the guidelines is to ensure that the effect sizes calculated from studies using different research designs are as similar as possible and have the same interpretive meaning as measures of the magnitude of effect of an intervention or practice. The particular formulas and methods described in this report are ones generally recommended for computing Cohen’s $d$ (Cohen, 1988). The thoughtful work of Dunlap et al. (1996), Rosenthal (1994), Sigurdsson and Austin (2004), Shadish et al. (2002), Swanson and Sachse-Lee (2000), and Thompson (2002, in press; Vacha-Haase & Thompson, 2004) informed the guidelines described in this paper.

**Effect Sizes**

An effect size is a measure of the magnitude of the strength of a relationship between an independent (intervention) and dependent (outcome) variable. Effect sizes are the preferred metric for estimating the magnitude of effect of an intervention or independent variable because they make possible between study as well as within study comparisons (Rosenthal, 1994). According to Thompson (2000), “interpreting the effect sizes in a given study facilitates the evaluation of how a study’s results fit into the existing literature, the explicit assessment of how similar or dissimilar results are across studies, and potentially informs judgment regarding what study features contributed to similarities and differences in effects” (p. 1, emphasis added).

There are two major classes or families of effect sizes as well as different indices within classes (see Rosenthal, 1994). Cohen’s $d$, the effect-size metric constituting the focus of this Centerscope article, is one of the most widely used measures of magnitude of effect. The formula for calculating Cohen’s $d$ is:

$$d = \frac{(M_1 - M_2)}{SD_p},$$

where

$M_1$ is the score mean of one group of study participants, $M_2$ is the score mean of a second group of study participants, and $SD_p$ is the pooled standard deviation for...
both groups of study participants. In instances where the groups have been exposed to different experiences (e.g., intervention), \( d \) is a measure of the magnitude of effect of the experience on the group receiving the enhanced opportunity.

There is still no generally agreed upon standards for interpreting the magnitude of effect sizes. Although Cohen’s (1977, 1988) original guidelines that \( d = .20 \) is a “small,” \( d = .50 \) is a “medium,” and \( d = .80 \) is a “large” effect size are still widely cited and used for interpreting magnitudes of effect (e.g., McCartney & Rosenthal, 2000), Glass, McGaw and Smith (1981) noted that “there is no wisdom…associating regions of the effect-size metric with descriptive adjectives such as ‘small,’ ‘moderate,’ ‘large,’ and the like” (p. 104). According to Lipsey (1998), however, an effect size of .20 “is a reasonable minimal effect size level to ask [intervention] research to detect—it is large enough to potentially represent an effect of practical significance, but not so small to represent an extreme outcome for intervention research” (p. 45).

Researchers’ exposure to effect sizes is often times done in the context of comparing randomly assigned study participants to experimental and control conditions where Cohen’s \( d \) is used to estimate the effect or benefit of the intervention or treatment provided to the experimental group participants. This often leads to a belief that calculating effect sizes are applicable only to these types of randomized design studies. This is not the case. As Thompson (2000) noted, because an effect size is a parametric measure and “parametric analyses are part of one general linear model family, and [they are all] correlational…effect sizes can be computed in all studies including, both experimental and non-experimental” (p. 2). As discussed next, the particular approach to conducting practice-based research syntheses we have developed for identifying evidence-based practice uses effect sizes as one means for ascertaining the particular practice characteristics that are associated with observed or reported differences on an outcome measure.

**Practice-Based Research Syntheses**

Practice-based research syntheses specifically focus on the characteristics or features of an intervention or environmental experience that are related to or are associated with variations in an outcome measure (Bronfenbrenner, 1992). The extent to which the same or similar characteristics behave or operate in the same way in different studies provides accumulated evidence about what really matters in terms of producing desired benefits. The more specific the characteristics, the more the research evidence directly informs the day-to-day practice of interventionists.

A practice-based research synthesis differs from more traditional reviews of research evidence by an explicit emphasis on unpacking and disentangling the characteristics, elements, and features of a practice (experience, opportunity, etc.) that account for the relationship between practice characteristics and desired benefits. Doing so directly informs what an individual (practitioner, parent, etc.) can do to produce a desired benefit.

Relating variations in practice characteristics to variations in outcomes can be accomplished using different research designs and different research methodologies (Dunst et al., 2002b). This means that any one practice-based research synthesis could include studies that used group and single-participant research designs, experimental and nonexperiential research designs, etc. (see e.g., Dunst, 2003).

**Effect Sizes**

Establishing and interpreting the relationship between practice characteristics and outcomes can be aided using effect sizes as a metric for ascertaining the relationship among variables. Practice-based research syntheses can include effect sizes as a way of both discerning strength of relationship among variables and identifying the particular practice characteristics that matter most in terms of explaining the relationship among variables (Dunst et al., 2002b). For example, in a practice-based reanalysis of a more traditional research synthesis (De Wolff & van Ijzendoorn, 1997), Kassow and Dunst (2004) used effect sizes as a means for identifying the particular features of parental sensitivity that were most related to secure infant attachment. Similarly, in a practice-based research synthesis of the influence of interest-based child learning on behavioral and developmental competence, Raab and Dunst (in press) used effect sizes to discern the extent to which personal compared to situational interests (Renninger, Hidi, & Krapp, 1992) had like or unlike influences on child outcome.

The usefulness of effect sizes as an interpretive device depends at least in part on the assumption that the effect sizes computed for individual studies included in a research synthesis have the same or similar meaning. This assumption is generally met when a synthesis includes studies that employed the same research design. This may not be the case in syntheses that include studies employing a variety of different research designs. The latter is what led us to prepare the guidelines in this *Centerscope* article. We have attempted to carefully select effect-size formulas that are applicable to different types of research designs so as to yield metrics that can be interpreted in the same manner.

**Effect-Size Formulas**

Different effect-size formulas require different information in order to calculate Cohen’s \( d \). Investigators are likely to find different terms and symbols for describing the means, standard deviations, and other statistics in research studies. For example, standard deviations may be represented as SD, \( sd \), \( s \), \( s \), or \( \sigma \).

Table 1 lists some of the terms, symbols, and statistics that are likely to be found in research reports. The terms and symbols used in the formulas below for calculating effect sizes are listed in the second column of the table. Subscripts are used in the different formulas to differentiate between different groups or statistics. For example, \( M_{E} \)
Table 1
Symbols and Terminology Typically Found in Research Reports

<table>
<thead>
<tr>
<th>Research Literature</th>
<th>Term/Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>M, X</td>
<td>M</td>
<td>Score mean of a dependent or outcome measure</td>
</tr>
<tr>
<td>SD, sd, S, s, σ</td>
<td>SD</td>
<td>Standard deviation of a score mean</td>
</tr>
<tr>
<td>se, SE</td>
<td>SE</td>
<td>Standard error of a score mean</td>
</tr>
<tr>
<td>N, n</td>
<td>N</td>
<td>Sample size or number of participants in a group or study</td>
</tr>
<tr>
<td>df</td>
<td>df</td>
<td>Degrees of freedom</td>
</tr>
<tr>
<td>t</td>
<td>t</td>
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<tr>
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</tr>
<tr>
<td>χ²</td>
<td>χ²</td>
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<tr>
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<td>r</td>
<td>Correlation</td>
</tr>
<tr>
<td>d</td>
<td>d</td>
<td>Cohen’s $d$ effect size</td>
</tr>
</tbody>
</table>

and $M_C$ are used to represent the score means of an experimental and comparison group, respectively. The last column of the table provides a brief description or explanation of the terms.

Table 2 lists formulas for calculating Cohen’s $d$ effect sizes for different types of studies using different information provided in research reports. The formulas are grouped into categories corresponding to independent group design studies, nonindependent-group design studies, single-participant design studies, and correlational design studies. The required information and statistics needed for using each formula is listed in the column rows. A user can easily select the appropriate formula by first determining the research design used in a study and by second using the information in the research report to select the appropriate formula for calculating Cohen’s $d$. The reader is referred to Shadish, Robinson and Lu (1997) and Thalheimer and Cook (2002, 2003) for computer software packages for calculating effect sizes. Clow and Dunst (2004) have developed EXCEL spreadsheets specifically for calculating effect sizes using the formulas included in this Centerscope article.

Calculating Effect Sizes for Two Independent Groups of Study Participants

The formulas included in this section are used for calculating effect sizes when you have statistical information for two different groups of study participants, and you want to know the magnitude of a treatment or intervention effect. The formulas yield Cohen’s $d$ for an experimental group vs. comparison group, treatment group vs. control group, intervention group vs. nonintervention group, etc. In most cases, the statistics used for calculating the effect size are for the measurements obtained after an intervention or treatment has been administered or experienced, where the effect size is a measure of the difference or advantage in the experimental group over and above that of the control or comparison group. In instances where there are pretest and posttest scores for the experimental and control groups, the effect-size computations are calculated for the posttest differences between groups.

Computing Effect Sizes from Means and Standard Deviations

The formula for calculating Cohen’s $d$ using the means and standard deviations for the two independent groups of study participants when either the sample sizes or the standard deviations are relatively equal is:

$$d = \frac{(M_E - M_C)}{\sqrt{(SD_E^2 + SD_C^2) / 2}},$$

where $M_E$ is the mean score of the experimental (intervention) group, $M_C$ is the mean score of the control (comparison) group, and $\sqrt{(SD_E^2 + SD_C^2) / 2}$ is the pooled standard deviation for the two groups of study participants. Computationally, $d$ is equal to the mean score of the experimental (intervention) group minus the mean score of the control (comparison) group divided by the pooled standard deviation for both groups of study participants. In cases where the sample sizes in the two groups are not relatively equal, the denominator term for calculating Cohen’s $d$ is:

$$\sqrt{\left[SD_E^2 \cdot N_E - 1 + SD_C^2 \cdot N_C - 1\right] / N_E + N_C - 2}.$$

Computing Effect Sizes from Means and Standard Errors

Research reports sometimes include standard errors of the mean scores for the experimental and comparison groups rather than standard deviations for the mean scores. The formula for calculating the effect size from mean scores and standard errors of the mean scores is:

$$d = \frac{(M_E - M_C)}{\sqrt{SE_E^2(N_E) + SE_C^2(N_C) / 2}},$$

where $M_E$ is the mean score of the experimental (intervention) group, $M_C$ is the mean score of the control (comparison) group, and $\sqrt{SE_E^2(N_E) + SE_C^2(N_C) / 2}$ is the pooled standard deviation computed from standard errors of the means.

Computing Effect Sizes from t Values and Sample Sizes

In instances where a research report includes both the Student’s $t$-test value for a between group comparison (e.g., experimental group vs. comparison group) and the
**Table 2**
**Formulas for Calculating Cohen’s d Effect Sizes for Different Research Designs**

<table>
<thead>
<tr>
<th>Formula</th>
<th>Required Information/Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
</tr>
</tbody>
</table>

**Independent Sample Designs**

1. $d = (M_E - M_C)/\sqrt{(SD_E^2 + SD_C^2)/2}$
   - ✓ ✓

2. $d = (M_E - M_C)/\sqrt{\left(SE_E^2(N_E) + SE_C^2(N_C)\right)/2}$
   - ✓ ✓

3. $d = t\sqrt{\left(N_E + N_C\right)/\left(N_E N_C\right)}$
   - ✓ ✓

4. $d = t(N_E + N_C)/(\sqrt{df})(\sqrt{N_E N_C})$
   - ✓ ✓ ✓

5. $d = 2t/\sqrt{df}$
   - ✓ ✓

6. $d = \sqrt{\left(4\chi^2\right)/(N - \chi^2)}$
   - ✓ ✓

**Nonindependent Sample Designs**

7. $d = (M_2 - M_1)/\sqrt{(SD_1^2 + SD_2^2)/2}$
   - ✓ ✓

8. $d = t\sqrt{2(1 - r)/N}$
   - ✓ ✓ ✓ ✓

**Single Participant Designs**

9. $d = (M_I - M_B)/\sqrt{(SD_B^2 + SD_I^2)/2}$
   - ✓ ✓

10. $d = (M_I - M_B)/(SD_p/\sqrt{2(1 - r)})$
    - ✓ ✓

**Correlational Designs**

11. $d = 2r/\sqrt{1 - r^2}$
    - ✓

12. $d = \left(\sqrt{\left(N_r^2 - 2N_T\right)/N_1 N_2}\right)(r/\sqrt{1 - r^2})$
    - ✓ ✓
sample sizes for both groups of study participants, the formula for calculating Cohen’s $d$ is:

$$d = t \left( \frac{N_E + N_C}{\sqrt{N_E N_C}} \right),$$

where $t$ is the Student’s $t$ value for the between group comparison, $N_E$ is the sample size of the experimental group, $N_C$ is the sample size of the comparison group, and the effect size is the $t$ value multiplied by the square root of the sample size term. In some cases, an analysis of variance F-test rather than a $t$-test will be used to make the between group comparison. The square root of the F-test is the $t$-test value ($\sqrt{F} = t$) used in Equation 3.

**Computing Effect Sizes from $t$ Values, Sample Sizes, and Degrees of Freedom**

Some research reports may include Student’s $t$-test values, sample sizes, and degrees of freedom. When these statistics are available, the formula for calculating $d$ is:

$$d = \frac{t(N_E + N_C)}{\sqrt{df}} \sqrt{\frac{N_E N_C}{N_E N_C}},$$

where $t$ is the Student’s $t$ value for the between group comparison, $N_E$ and $N_C$ are the number of participants in the experimental and comparison groups, respectively, and $df$ is the degrees of freedom from the $t$ test. The effect size is calculated by multiplying the $t$ value by the total sample size ($N_E + N_C$) divided by the product of the square root of the degrees of freedom and the square root of the product of the two sample sizes. The degrees of freedom ($df$) for the calculation is $(N_E + N_C - 2)$.

**Computing Effect Sizes from $t$ Values and Degrees of Freedom**

In cases where the sample sizes of both the experimental and comparison groups are relatively equal and information is available to ascertain the degrees of freedom of the $t$-test comparison, the formula for calculating $d$ is:

$$d = \frac{2t}{\sqrt{df}},$$

where $t$ is the Student’s $t$ value for the between group comparison and $df$ is the number of degrees of freedom for the $t$ test. The degrees of freedom are equal to $(N_E + N_C) - 2$, where $N_E$ is the number if participants in the experimental group and $N_C$ is the number of participants in the comparison group.

In some cases you may be able to ascertain the total number of participants in a study but not be able to know if the sample sizes for the two groups of study participants are equal. Formula 5 can be used to calculate Cohen’s $d$, but will likely overestimate the magnitude of effect.

**Calculating Effect Sizes from Chi Square Statistics**

There are sometimes instances where both an independent variable and outcome variable or measure are both measured dichotomously. In this case, a Chi-square test is often used to evaluate whether the proportions of participants in two groups (e.g., experimental group vs. comparison groups) differ on the presence or absence of some criterion measure (e.g., high vs. low blood pressure). Cohen’s $d$ effect size for the $\chi^2$ can be calculated using the formula:

$$d = \sqrt{\frac{4 \chi^2}{(N - \chi^2)}},$$

where the square root of four (4) times the $\chi^2$ value is divided by the total sample size in the study minus the $\chi^2$ value.

**Calculating Effect Sizes for Nonindependent Groups of Study Participants**

The procedures included in this section are for calculating effect sizes when the same group of participants are measured on two separate occasions (e.g., pretest vs. posttest) or the same group of participants are measured under contrasting conditions (e.g., child-initiated learning vs. adult-directed learning) where one condition is hypothesized to be related to better performance on a dependent measure. The nonindependent-group design formulas are also used if participants in the two groups are matched on some third variable (e.g., child developmental quotients).

**Computing Effect Sizes from Means and Standard Deviations**

The formula for calculating Cohen’s $d$ from the means and standard deviations for the two measurement occasions is:

$$d = \frac{(M_2 - M_1)}{\sqrt{(SD_1^2 + SD_2^2)/2}},$$

where $M_2$ is the mean posttest score or mean score of the measure that is expected to be positively related to the independent variable, $M_1$ is the pretest or comparison group mean score, and $\sqrt{(SD_1^2 + SD_2^2)/2}$ is the pooled standard deviation for the two measurement occasions. Formula 7 is applicable to situations where the correlation between the two sets of scores is small. When this is not the case, Formula 8 should be used to calculate the magnitude of effect.

**Computing Effect Sizes from $t$ Values and Study Sample Sizes**

In cases where a research report includes the Student’s $t$-test is used for the pretest/post-test or matched groups comparison, the correlation for the two sets of scores, and the sample sizes are reported or can be ascertained, a special formula can be used to calculate Cohen’s $d$ so as to not overestimate the magnitude of effect (Dunlap et al., 1996). The formula is:
\[ d = t \sqrt{\frac{2(1-r)}{N}}, \]  

(8)

where 

\( t \) is the Student’s \( t \) value for the between measurement occasion comparison, \( r \) is the correlation between the two sets of measures, and \( N \) is the number of study participants.

### Calculating Effect Sizes from Single-Participant Research Design Studies

The procedures described in this section are for calculating effect sizes for single-participant design studies that have both baseline (pretest) and intervention (posttest) phase data (Sigurdsson & Austin, 2004; Swanson & Sachse-Lee, 2000). In a few cases, raw data may be presented in a research report that can be used to calculate needed statistics. In most cases, the data will need to be estimated from graphs displaying patterns of findings. In order to calculate effect sizes from single-participant research design studies, a sufficient number of data points need to be available to calculate the statistics needed to use either formula (see below).

There is considerable controversy surrounding, and objections about, calculating effect sizes from single-participant design studies (see e.g., Busk & Serlin, 1992; Faith, Allison, & Gorman, 1997; Salzberg, Strain, & Baer, 1987; Scruggs & Mastropieri, 2001). Our main purpose in calculating magnitude of treatment effects in single-participant design studies is to produce a metric that is comparable to effect sizes computed from data in studies using other types of research designs.

The particular formulas we have included in the guidelines are applicable for different sets of conditions. If the “spread of scores” in the baseline and intervention phases are varied and the correlation between the baseline vs. intervention phase and dependent measures is small, Formula 9 can be used to calculate Cohen’s \( d \). If the baseline and intervention phase data are mostly nonoverlapping or the correlation between the baseline vs. intervention phases and dependent measures is large, Formula 10 should be used.

A decision about which formula to use should be done by first calculating the means and standard deviations for the baseline and intervention phases and the correlation between the baseline condition coded zero (0) and the intervention phase condition coded one (1) and the dependent measures of both phases of data. With those results, you can decide which formula to use to code Cohen’s \( d \).

### Computing Effect Sizes from Mean Scores and Pooled Standard Deviations

Sigurdsson and Austin (2004) and Swanson and Sachse-Lee (2000) both recommend that the effect sizes for intervention vs. baseline phase single-participant design study data be calculated using the pooled standard deviations for estimating the magnitude of intervention effect. In instances where there is reasonable spread in the baseline and intervention phase data and the correlation between conditions and the dependent measures is small, Formula 9 should be used to calculate the effect size. In many cases, the baseline or intervention phase data may include one or more outliers. This is not uncommon in single-participant design studies. Although it is tempting to exclude the outliers in calculating standard deviations, this should not be done unless there is an identifiable cause or reason for the aberrant response or behavior that can reasonably be explained.

The formula for calculating an effect size when the above conditions are met is:

\[ d = \left( M_I - M_B \right) / \sqrt{\left( SD_P^2 + SD_I^2 \right) / 2}, \]  

(9)

where \( M_I \) is the mean score for the intervention phase data, \( M_B \) is the mean score for the baseline phase data, and \( \sqrt{\left( SD_P^2 + SD_I^2 \right) / 2} \) is the pooled standard deviation.

### Calculating Effect Sizes from the Correlations Between the Baseline and Intervention Phase Data

Many single-participant research design studies produce findings where the correlation between baseline vs. intervention phases and the dependent measure is high (Swanson & Sachse-Lee, 2000). Dunlap et al. (1996) has shown that where contrasting conditions data are correlated, effect-size calculations yield overestimates of the magnitude of effect of the intervention. The correlation between the baseline and intervention phase data will especially be inflated when the spread of scores is small, the percentage of scores or measures for the two conditions are nonoverlapping, and the correlation between conditions and the dependent measures is large.

The formula for calculating an effect size from single-participant design studies where one or more of these situations are present is:

\[ d = \left( M_I - M_B \right) / \left( SD_P / \sqrt{2(1-r)} \right), \]  

(10)

where \( M_I \) is the mean score for the intervention phase data, \( M_B \) is the mean score for the baseline phase data, \( SD_P \) is the pooled standard deviation for both data phases (calculated in the manner shown in Formula 9), and \( r \) is the correlation between the baseline and intervention phase data.

### Converting Correlation Coefficients to Effect Sizes

In some cases, research reports will include correlation coefficients for showing the relationship between an independent variable and a dependent or outcome measure. These may include Pearson’s product moment correlations, point biserial correlations or biserial correlations. The formulas in this section permit conversion of correlation coefficients to effect sizes for different kinds of designs and analyses.

There are two types of correlational research designs that are most likely to be encountered in conducting a
Cohen's outcome measure for the correlation coefficient to an effect size (Aaron, Kromrey, & Ferron, 1998; Thompson, 2000).

**Computing Effect Sizes from Correlation Coefficients in Equal Sample Size Studies**

In cases where the sample sizes for experimental and comparison groups are relatively equal, or variations in practice characteristics are correlated with variations in an outcome measure for the same group of study participants, Cohen’s $d$ can be calculated using the formula:

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

(11)

where $r$ is the correlation coefficient, and the effect size $d$ is determined by multiplying $r$ by two (2) and dividing by the square root of 1(one) minus $r$ squared. Alternatively, you can use the Appendix to convert a correlation coefficient to an effect size. Simply find the $r$ that matches the one in the research report and convert it to the corresponding $d$ values.

**Computing Effect Sizes from Correlation Coefficients in Unequal Sample Size Studies**

In cases where the sample sizes for experimental and comparison groups are not relatively equal, the formula for converting a correlation coefficient to Cohen’s $d$ is:

$$d = \left( \frac{N_1^2 - 2N_T}{N_1N_2} \right) \left( \frac{r}{\sqrt{1 - r^2}} \right),$$

(12)

where $N_1$ is the total number of study participants ($N_1 + N_2$), $N_1$ and $N_2$ are the sample sizes for the two groups of study participants, and $r$ is the correlation coefficient between the groups coded dichotomously and related to variations in an outcome measure.

**Converting Probability Levels to Effect Sizes**

In some cases, research reports include only p-values for the differences between score means. The reported probability level can be converted to an effect size using a normal curve table. The procedures for doing so are described in Rosenthal (1994). Although this method yields less accurate effect sizes, it sometimes is the only way to calculate the magnitude of effect for study results. The procedure should be used only when Cohen’s $d$ cannot be calculated using more accurate computational methods.

**Conclusions**

The purpose of this Centerscope article is to describe procedures for calculating Cohen’s $d$ effect sizes in studies using different research designs so as to be able to have a common metric for ascertaining the magnitude and nature of the relationship between the practice characteristics and outcomes in a study. The guidelines ensure that the effect sizes calculated from different research designs have similar interpretive meaning.

In cases where practice-based research syntheses include studies using different research designs, explicitly determining whether bias may be present for differences in computational methods should be done as part of the interpretive process (Shadish et al., 2002). Therefore, the magnitude and patterns of effect sizes for different research designs and different effect-size formulas should be compared to ensure no one procedure produces biased indices. The reader should be aware that there are other possible biases that may lead to misinterpretations of effect sizes. Shadish et al. (2002, Appendix 13.1) describe several threats to inferences made from study findings that involve effect-size computations.

**Implications**

A practice-based research synthesis is concerned with both the characteristics and consequences of practice variables and how variations in characteristics are related to variations in outcomes (Dunst et al., 2002b). There are three primary implications for using effect sizes for discerning the nature of these relationships.

One implication of effect sizes in practice-based research syntheses is to isolate those practice characteristics that matter most in explaining variations in an outcome measure. Effect sizes provide one way of determining among any number of related practice characteristics, which ones best explain study results and therefore are the characteristics that make more explicit what intervention practices ought to look like to produce desired effects (Kassow & Dunst, 2004).

A second implication of effect sizes in practice-based research syntheses is determining the strength of relationship between particular kinds of practice characteristics and specific outcomes. The usefulness of research evidence for informing practice is, in part, determined by the probability that a given practice will produce a desired effect. The magnitude of effect can help inform the likelihood of a practice having a minor or major impact.

A third implication of effect sizes in practice-based research syntheses is to establish which kinds of practices have like or unlike effects in different outcomes. This is done, for example, by comparing the effect sizes for the relationship between variations in practice characteristics for related but different outcome measures (e.g., language production vs. language comprehension). Doing so can
help isolate what effects the intervention is likely and not likely to produce.

**Summary**

A major goal of a practice-based research synthesis is increased understanding of how different kinds of environmental variables influence behavior and development. Effect sizes are one "tool" that can be used for informing the nature of these relationships. The procedures and guidelines described in this article facilitate this process.

**References**


work-learning.com/effect_sizes.htm.


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## Appendix

*Conversion Table for Determining Cohen’s $d$ Effect Sizes from a Correlation Coefficient Coefficients*

<table>
<thead>
<tr>
<th>$r$</th>
<th>$d$</th>
<th>$r$</th>
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