9.1 DEFINITION OF MEDIATION

Mediation involves a set of causal hypotheses. An initial causal variable $X_1$ may influence an outcome variable $Y$ through a mediating variable $X_2$. (Some books and websites use different notations for the three variables; for example, on Kenny's mediation webpage, http://www.davidakenny.net/cm/mediate.htm, the initial causal variable is denoted $X$, the outcome as $Y$, and the mediating variable as $M$.) Mediation occurs if the effect of $X_1$ on $Y$ is partly or entirely “transmitted” by $X_2$. A mediated causal model involves a causal sequence; first, $X_1$ causes or influences $X_2$; then, $X_2$ causes or influences $Y$. $X_1$ may have additional direct effects on $Y$ that are not transmitted by $X_2$. A mediation hypothesis can be represented by a diagram of a causal model. Note that the term causal is used because the path diagram represents hypotheses about possible causal influence; however, when data come from nonexperimental designs, we can only test whether a hypothesized causal model is consistent or inconsistent with a particular causal model. That analysis falls short of proof that any specific causal model is correct.

9.1.1 Path Model Notation

Path model notation was introduced earlier and it is briefly reviewed here. We begin with two variables ($X$ and $Y$). Arrows are used to correspond to paths that represent different types of relations between variables. The absence of an arrow between $X$ and $Y$ corresponds to an assumption that these variables are not related in any way; they are not correlated or confounded, and they are not directly causally connected. A unidirectional arrow corresponds to the hypothesis that one variable has a causal influence on the other—for example, $X \rightarrow Y$ corresponds to the hypothesis that $X$ causes or influences $Y$; $Y \rightarrow X$ corresponds to the hypothesis that $Y$ causes or influences $X$. A bidirectional or double-headed arrow represents a noncausal association, such as correlation or confounding of variables that does not arise from any causal connection between them. In path diagrams, these double-headed arrows may be shown as curved lines.

If we consider only two variables, $X$ and $Y$, there are four possible models: (a) $X$ and $Y$ are not related in any way (this is denoted in a path diagram by the absence of a path between $X$ and $Y$), (b) $X$ causes $Y$ ($X \rightarrow Y$), (c) $Y$ causes $X$ ($Y \rightarrow X$), and (d) $X$ and $Y$ are correlated but not because of any causal influence ($XY$). When a third variable is added, the number of possible relationships among the variables $X_1$, $X_2$, and $Y$ increases substantially. One theoretical model corresponds to $X_1$ and $X_2$ as correlated causes of $Y$. For this model, the appropriate analysis is a regression to predict $Y$ from both $X_1$ and $X_2$. Another possible hypothesis is that $X_2$ may be a moderator of the relationship between $X_1$ and $Y$; this is also described as an interaction
between $X_1$ and $X_2$ as predictors of $Y$. Statistical significance and nature of interaction can be assessed using procedures described in Chapter 7, on moderation.

### 9.1.2 Circumstances in Which Mediation May Be a Reasonable Hypothesis

Because a mediated causal model includes the hypothesis that $X_1$ causes or influences $X_2$ and the hypothesis that $X_2$ causes or influences $Y$, it does not make sense to consider mediation analysis in situations where one or both hypotheses would be nonsense. For $X_1$ to be hypothesized as a cause of $X_2$, $X_1$ should occur before $X_2$, and there should be a plausible mechanism through which $X_1$ could influence $X_2$. For example, suppose we are interested in a possible association between height and salary (a few studies suggest that taller people earn higher salaries). It is conceivable that height influences salary (perhaps employers have a bias that leads them to pay tall people more money). It is not conceivable that a person's salary changes his or her height.

### 9.2 HYPOTHETICAL RESEARCH EXAMPLE

This hypothetical correlational study examines associations among three variables as an illustration of a mediation hypothesis: $X_1$, age; $X_2$, body weight; and $Y$, systolic blood pressure (SBP). The data are in an SPSS file named ageweightbp.sav. Note that for research applications of mediation analysis, much larger sample sizes should be used.

For these variables, it is plausible to hypothesize the following causal connections. Blood pressure tends to increase as people age. As people age, body weight tends to increase (this could be due to lower metabolic rate, reduced activity level, or other factors). Other factors being equal, increased body weight makes the cardiovascular system work harder, and this can increase blood pressure. It is possible that at least part of the age-related increase in blood pressure might be mediated by age-related weight gain. Figure 9.1 is a path model that represents this mediation hypothesis for this set of three variables.

To estimate the strength of association that corresponds to each path in Figure 9.1, a series of three ordinary least squares (OLS) linear regression analyses can be run. Note that a variable is dependent if it has one or more unidirectional arrows pointing toward it. We run a regression analysis for each dependent variable (such as $Y$), using all variables that have unidirectional arrows that point toward $Y$ as predictors. For the model in Figure 9.1, the first regression predicts $Y$ from $X_1$ (blood pressure from age). The second regression predicts $X_2$ from $X_1$ (weight from age). The third regression predicts $Y$ from both $X_1$ and $X_2$ (blood pressure predicted from both age and weight).

### 9.3 LIMITATIONS OF “CAUSAL” MODELS

Path models similar to Figure 9.1 are called “causal” models because each unidirectional arrow represents a hypothesis about a possible causal connection between two variables. However, the data used to estimate the strength of relationship for the paths are almost always from nonexperimental studies, and nonexperimental data cannot prove causal hypotheses. If the path coefficient between two variables such as $X_2$ and $Y$ (this coefficient is denoted $b$ in Figure 9.1) is statistically significant and large enough in magnitude to indicate a change in the outcome variable that is clinically or practically important, this result is consistent with the possibility that $X_2$ might cause $Y$, but it is not proof of a causal connection. Numerous other situations could yield a large path coefficient between $X_2$ and $Y$. For example, $Y$ may cause $X_2$; both $Y$ and $X_2$ may be
caused by some third variable, $X_3$; $X_2$ and $Y$ may actually be measures of the same variable; the relationship between $X_1$ and $Y$ may be mediated by other variables, $X_4$, $X_5$, and so on; or a large value for the $b$ path coefficient may be due to sampling error.

### 9.3.1 Reasons Why Some Path Coefficients May Be Not Statistically Significant

If the path coefficient between two variables is not statistically significantly different from zero, there are also several possible reasons. If the $b$ path coefficient in Figure 9.1 is close to zero, this could be because there is no causal or noncausal association between $X_1$ and $Y$. However, a small path coefficient could also occur because of sampling error or because assumptions required for regression are severely violated.

### 9.3.2 Possible Interpretations for Statistically Significant Paths

A large and statistically significant $b$ path coefficient is consistent with the hypothesis that $X_1$ causes $Y$, but it is not proof of that causal hypothesis. Replication of results (such as values of $a$, $b$, and $c'$ path coefficients in Figure 9.1) across samples increases confidence that findings are not due to sampling error. For predictor variables and/or hypothesized mediating variables that can be experimentally manipulated, experimental studies can be done to provide stronger evidence whether associations between variables are causal (MacKinnon, 2008). By itself, a single mediation analysis only provides preliminary nonexperimental evidence to evaluate whether the proposed causal model is plausible (i.e., consistent with the data).
9.4 QUESTIONS IN A MEDIATION ANALYSIS

Researchers typically ask two questions in a mediation analysis. The first question is whether there is a statistically significant mediated path from $X_1$ to $Y$ via $X_2$ (and whether the part of the $Y$ outcome variable score that is predictable from this path is large enough to be of practical importance). Recall from the discussion of the tracing rule in Chapter 4 that when a path from $X$ to $Y$ includes more than one arrow, the strength of the relationship for this multiple-step path is obtained by multiplying the coefficients for each included path. Thus, the strength of the mediated relationship (the path from $X_1$ to $Y$ through $X_2$ in Figure 9.1) is estimated by the product of the $a \times b$ ($ab$) coefficients. The null hypothesis of interest is $H_0: ab = 0$. Note that the unstandardized regression coefficients are used for this significance test. Later sections in this chapter describe test statistics for this null hypothesis. If this mediated path is judged to be nonsignificant, the mediation hypothesis is not supported, and the data analyst would need to consider other explanations.

If there is a significant mediated path (i.e., the $ab$ product differs significantly from zero), then the second question in the mediation analysis is whether there is also a significant direct path from $X_1$ to $Y$; this path is denoted $c'$ in Figure 9.1. If $c'$ is not statistically significant (or too small to be of any practical importance), a possible inference is that the effect of $X_1$ on $Y$ is completely mediated by $X_2$. If $c'$ is statistically significant and large enough to be of practical importance, a possible inference is that the influence of $X_1$ on $Y$ is only partially mediated by $X_2$, and that $X_1$ has some additional effect on $Y$ that is not mediated by $X_2$. In the hypothetical data used for the example in this chapter (in the SPSS file ageweightbp.sav), we will see that the effects of age on blood pressure are only partially mediated by body weight.

Of course, it is possible that there could be additional mediators of the effect of age on blood pressure; for example, age-related changes in the condition of arteries might also influence blood pressure. Models with multiple mediating variables are discussed briefly later in the chapter.

9.5 ISSUES IN DESIGNING A MEDIATION ANALYSIS STUDY

A mediation analysis begins with a minimum of three variables. Every unidirectional arrow that appears in Figure 9.1 represents a hypothesized causal connection and must correspond to a plausible theoretical mechanism. A model such as age $\rightarrow$ body weight $\rightarrow$ blood pressure seems reasonable; processes that occur with advancing age, such as slowing metabolic rate, can lead to weight gain, and weight gain increases the demands on the cardiovascular system, which can cause an increase in blood pressure. However, it would be nonsense to propose a model of the following form: blood pressure $\rightarrow$ body weight $\rightarrow$ age, for example; there is no reasonable mechanism through which blood pressure could influence body weight, and weight cannot influence age in years.

9.5.1 Types of Variables in Mediation Analysis

Usually all three variables ($X_1$, $X_2$, and $Y$) in a mediation analysis are quantitative. A dichotomous variable can be used as a predictor in regression (Chapter 6), and therefore it is acceptable to include an $X_1$ variable that is dichotomous (e.g., treatment vs. control) as the initial causal variable in a mediation analysis; OLS regression methods can still be used in this situation. However, both $X_2$ and $Y$ are dependent variables in mediation analysis; if one or both of these variables are categorical, then logistic regression is needed to estimate regression coefficients, and this complicates the interpretation of outcomes (see MacKinnon, 2008, Chapter 11).

It is helpful if scores on the variables can be measured in meaningful units because this makes it easier to evaluate whether the strength of influence indicated by path coefficients is
large enough to be clinically or practically significant. For example, suppose that we want to predict annual salary in dollars ($Y$) from years of education ($X_1$). An unstandardized regression coefficient is easy to interpret. A student who is told that each additional year of education predicts a $50 increase in annual salary will understand that the effect is too weak to be of any practical value, while a student who is told that each additional year of education predicts a $5,000 increase in annual salary will understand that this is enough money to be worth the effort. Often, however, measures are given in arbitrary units (e.g., happiness rated on a scale from $1 = \text{not happy at all}$ to $7 = \text{extremely happy}$). In this kind of situation, it may be difficult to judge the practical significance of a half-point increase in happiness.

As in other applications of regression, measurements of variables are assumed to be reliable and valid. If they are not, regression results can be misleading.

9.5.2 Temporal Precedence or Sequence of Variables in Mediation Studies

Hypothesized causes must occur earlier in time than hypothesized outcomes (temporal precedence, as discussed in Volume I, Chapter 2 [Warner, 2020]). It seems reasonable to hypothesize that “being abused as a child” might predict “becoming an abuser as an adult”; it would not make sense to suggest that being an abusive adult causes a person to have experiences of abuse in childhood. Sometimes measurements of the three variables $X_1, X_2,$ and $Y$ are all obtained at the same time (e.g., in a one-time survey). If $X_1$ is a retrospective report of experiencing abuse as a child, and $Y$ is a report of current abusive behaviors, then the requirement for temporal precedence ($X_1$ happened before $Y$) may be satisfied. In some studies, measures are obtained at more than one point in time; in these situations, it would be preferable to measure $X_1$ first, then $X_2$, and then $Y$; this may help establish temporal precedence. When all three variables are measured at the same point in time and there is no logical reason to believe one of them occurs earlier in time than the others, it may not be possible to establish temporal precedence.

9.5.3 Time Lags Between Variables

When measures are obtained at different points in time, it is important to consider the time lag between measures. If this time lag is too brief, the effects of $X_1$ may not be apparent yet when $Y$ is measured (e.g., if $X_1$ is initiation of treatment with either placebo or Prozac, a drug that typically does not have full antidepressant effects until about 6 weeks, and $Y$ is a measure of depression and is measured one day after $X_1$, then the full effect of the drug will not be apparent). Conversely, if the time lag is too long, the effects of $X_1$ may have worn off by the time $Y$ is measured. Suppose that $X_1$ is receiving positive feedback from a relationship partner and $Y$ is relationship satisfaction, and $Y$ is measured 2 months after $X_1$. The effects of the positive feedback ($X_1$) may have dissipated over this period of time. The optimal time lag will vary depending on the variables involved; some $X_1$ interventions or measured variables may have immediate but not long-lasting effects, while others may require a substantial time before effects are apparent.

9.6 ASSUMPTIONS IN MEDIATION ANALYSIS AND PRELIMINARY DATA SCREENING

Unless the types of variables involved require different estimation methods (e.g., if a dependent variable is categorical, logistic regression methods are required), the coefficients ($a$, $b$, and $c'$) associated with the paths in Figure 9.1 can be estimated using OLS regression. All of the assumptions required for regression (see Volume I, Chapter 11 [Warner, 2020], and Chapter 5 in the present volume) are also required for mediation analysis. Because preliminary data screening
was presented in greater detail earlier, data-screening procedures are reviewed here only briefly. For each variable, histograms or other graphic methods can be used to assess whether scores on all quantitative variables are reasonably normally distributed, without extreme outliers. If the \( X_1 \) variable is dichotomous, both groups should have a reasonably large number of cases. Scatterplots can be used to evaluate whether relationships between each pair of variables appear to be linear (\( X_1 \) with \( Y \), \( X_1 \) with \( X_2 \), and \( X_2 \) with \( Y \)) and to identify bivariate outliers.

Baron and Kenny (1986) suggested that a mediation model should not be tested unless there is a significant relationship between \( X_1 \) and \( Y \). In more recent treatments of mediation, it has been pointed out that in situations where one of the path coefficients is negative, there can be significant mediated effects even when \( X_1 \) and \( Y \) are not significantly correlated (Hayes, 2009). This can be understood as a form of suppression. If none of the pairs of variables in the model are significantly related to one another in bivariate analyses, however, there is not much point in testing mediated models.

MacKinnon, Krull, and Lockwood (2000) explained that the patterns of results obtained from analysis of models such as the models presented here for partial or complete mediation cannot prove mediation hypotheses. The patterns of results that might be interpreted as evidence of mediation are equally consistent with the outcomes expected for suppression and confounded predictor. Empirical results do not make it possible to distinguish which of these explanations is “better.”

### 9.7 PATH COEFFICIENT ESTIMATION

The most common way to obtain estimates of the path coefficients that appear in Figure 9.1 is to run the following series of regression analyses. These steps are similar to those recommended by Baron and Kenny (1986), except that, as suggested in recent treatments of mediation (MacKinnon, 2008), a statistically significant outcome on the first step is not considered a requirement before going on to subsequent steps.

**Step 1:** First, a regression is run to predict \( Y \) (SBP) from \( X_1 \) (age). (SPSS procedures for this type of regression were provided in Volume I, Chapter 11 [Warner, 2020], and Chapter 4 in the present volume.) The raw or unstandardized regression coefficient from this regression corresponds to path \( c \). This step is sometimes omitted; however, it provides information that can help evaluate how much controlling for the \( X_1 \) mediating variable reduces the strength of association between \( X_1 \) and \( Y \). Figure 9.2 shows the regression coefficients part of the output. The unstandardized regression coefficient for the prediction of \( Y \) (BloodPressure—note that there is no space within the SPSS variable name) from \( X_1 \) (age) is \( c = 2.862 \); this is statistically significant, \( t(28) = 6.631, p < .001 \). (The \( N \) for this data set is 30; therefore, the \( df \) for this \( t \) ratio is \( N – 2 = 28 \).) Thus, the overall effect of age on blood pressure is statistically significant.

**Step 2:** Next a regression is performed to predict the mediating variable (\( X_2 \), weight) from the causal variable (\( X_1 \), age). The results of this regression provide the path coefficient for the path denoted \( a \) in Figure 9.1 and also the standard error of \( a \) (\( se_a \)) and the \( t \) test for the statistical significance of the \( a \) path coefficient (\( ta \)). The coefficient table for this regression appears in Figure 9.3. For the hypothetical data, the unstandardized \( a \) path coefficient was 1.432, with \( t(28) = 3.605, p = .001 \).

**Step 3:** Finally, a regression is performed to predict the outcome variable \( Y \) (blood pressure) from both \( X_1 \) (age) and \( X_2 \) (weight). (Detailed examples of regression with two predictor variables appeared in Chapter 4.) This regression provides estimates of the unstandardized coefficients for path \( b \) (and \( sb \) and \( tb \)) and also path \( c' \) (the direct or remaining effect of \( X_1 \) on \( Y \) when the mediating variable has been included in the analysis). See Figure 9.1 for the corresponding path diagram. From Figure 9.4, path
These unstandardized path coefficients are used to label the paths in a diagram of the causal model (top panel of Figure 9.5). These values are also used later to test the null hypothesis $H_0: ab = 0$. In many research reports, particularly when the units in which the variables are measured are not meaningful or not easy to interpret, researchers report the standardized path coefficients (these are called beta coefficients in the SPSS output); the bottom panel of Figure 9.5 shows the standardized path coefficients. Sometimes the estimate of the $c$ coefficient appears in parentheses, next to or below the $c'$ coefficient, in these diagrams.

In addition to examining the path coefficients from these regressions, the data analyst should pay some attention to how well the $X_1$ and $X_2$ variables predict $Y$. From Figure 9.4, $R^2 = .69$, adjusted $R^2 = .667$, and this is statistically significant, $F(2, 27) = 30.039, p < .001$. These two variables do a good job of predicting variance in blood pressure.

9.8 CONCEPTUAL ISSUES: ASSESSMENT OF DIRECT VERSUS INDIRECT PATHS

When a path that leads from a predictor variable $X$ to a dependent variable $Y$ involves other variables and multiple arrows, the overall strength of the path is estimated by multiplying the

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**Figure 9.2** Regression Coefficient to Predict Blood Pressure ($Y$) From Age ($X_1$)

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>Std. Error</td>
</tr>
<tr>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Constant)</td>
<td>10.398</td>
<td>26.222</td>
</tr>
<tr>
<td>Age</td>
<td>2.862</td>
<td>.432</td>
</tr>
</tbody>
</table>

Note: The raw-score slope in this equation, 2.862, corresponds to coefficient $c$ in the path diagram in Figure 9.1.

**Figure 9.3** Regression Coefficient to Predict Weight (Mediating Variable $X_2$) From Age ($X_1$)

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>Std. Error</td>
</tr>
<tr>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Constant)</td>
<td>78.508</td>
<td>24.130</td>
</tr>
<tr>
<td>Age</td>
<td>1.432</td>
<td>.397</td>
</tr>
</tbody>
</table>

Note: The raw-score slope from this equation, 1.432, corresponds to the path labeled $a$ in Figure 9.1.
coefficients for each leg of the path (as discussed in the introduction to the tracing rule in Chapter 4).

9.8.1 The Mediated or Indirect Path: \( ab \)

The strength of the indirect or mediated effect of age on blood pressure through weight is estimated by multiplying the \( ab \) path coefficients. In many applications, one or more of the variables are measured in arbitrary units (e.g., happiness may be rated on a scale from 1 to 7). In such situations, the unstandardized regression coefficients may not be very informative, and research reports often focus on standardized coefficients. The standardized (\( \beta \)) coefficients for the paths in the age, weight, and blood pressure hypothetical data appear in the bottom panel of Figure 9.5. Throughout the remainder of this section, all path coefficients are given in standardized (\( \beta \)-coefficient) form.

When the path from \( X \) to \( Y \) has multiple parts or arrows, the overall strength of the association for the entire path is estimated by multiplying the coefficients for each part of the path. Thus, the unit-free index of strength of the mediated effect (the effect of age on blood pressure, through the mediating variable weight) is given by the product of the standardized...
estimates of the path coefficients, $ab$. For the standardized coefficients, this product $= (.563 \times .340) = .191$. The strength of the direct or nonmediated path from age to SBP corresponds to $c'$; the standardized coefficient for this path is .590. In other words, for a 1-SD increase in $z_{\text{Age}}$, we predict a .191 increase in $z_{\text{SBP}}$ through the mediating variable $z_{\text{Weight}}$. In addition, we predict a .590 increase in $z_{\text{SBP}}$ due to direct effects of $z_{\text{Age}}$ (effects that are not mediated by $z_{\text{Weight}}$); this corresponds to the $c'$ path. The total effect of $z_{\text{Age}}$ on $z_{\text{SBP}}$ corresponds to path $c$, and the standardized coefficient for path $c$ is .782 (the beta coefficient to predict $z_{\text{SBP}}$ from $z_{\text{Age}}$ in Figure 9.5).

### 9.8.2 Mediated and Direct Path as Partition of Total Effect

The mediation analysis has partitioned the total effect of age on blood pressure ($c = .782$) into a direct effect ($c' = .590$) and a mediated effect ($ab = .191$). (Both of these are given in terms of standardized or unit-free path coefficients.) It appears that mediation through weight, while statistically significant, explains only a small part of the total effect of age on blood pressure in this hypothetical example. Within rounding error, $c = c' + ab$, that is, the total effect is the sum of the direct and mediated effects. These terms are additive when OLS regression is used to obtain estimates of coefficients; when other estimation methods such as maximum likelihood are used (as in structural equation modeling [SEM] programs), these equalities may not hold. Also note that if there are missing data, each regression must be performed on the same set of cases in order for this additive association to work.

Note that even if the researcher prefers to label and discuss paths using standardized regression coefficients, information about the unstandardized coefficients is required to carry
out additional statistical significance tests (to find out whether the product $ab$ differs significantly from zero, for example).

### 9.8.3 Magnitude of Mediated Effect

When variables are measured in meaningful units, it is helpful to think through the magnitude of the effects in real units, as discussed in this paragraph. (The discussion in this paragraph is helpful primarily in research situations in which units of measurement have some real-world practical interpretation.) All of the path coefficients in the rest of this paragraph are unstandardized regression coefficients. From the first regression analysis, the $c$ coefficient for the total effect of age on blood pressure was $c = 2.862$. In simple language, for each 1-year increase in age, we predict an increase in blood pressure of 2.862 mm Hg. On the basis of the $t$-test result in Figure 9.2, this is statistically significant. Taking into account that people in wealthy countries often live to age 70 or older, this implies substantial age-related increases in blood pressure; for example, for a 30-year increase in age, we predict an increase of 85.86 mm Hg in blood pressure, and that is sufficiently large to be clinically important. This tells us that the total effect of age on SBP is reasonably large in terms of clinical or practical importance. From the second regression, we find that the effect of age on weight is $a = 1.432$; this is also statistically significant, on the basis of the $t$ test in Figure 9.3. For a 1-year increase in age, we predict almost 1.5 lb in weight gain. Again, over a period of 10 years, this implies a sufficiently large increase in predicted body weight (about 14.32 lb) to be of clinical importance. The last regression (in Figure 9.4) provides information about two paths, $b$ and $c'$. The $b$ coefficient that represents the effect of weight on blood pressure was $b = .49$; this was statistically significant. For each 1-lb increase in weight, we predict almost a half-point increase in blood pressure. If we take into account that people may gain 30 or 40 lb over the course of a lifetime, this would imply weight-related increases in blood pressure on the order of 15 or 20 mm Hg. This also seems large enough to be of clinical interest. The indirect effect of age on blood pressure is found by multiplying $a \times b$, in this case, $1.432 \times .49 = .701$. For each 1-year increase in age, a .7 mm Hg increase in blood pressure is predicted through the effects of age on weight. Finally, the direct effect of age on blood pressure when the mediating variable weight is statistically controlled or taken into account is represented by $c' = 2.161$. Over and above any weight-related increases in blood pressure, we predict a 2.2-unit increase in blood pressure for each additional year of age. Of the total effect of age on blood pressure (a predicted 2.862 mm Hg increase in SBP for each 1-year increase in age), a relatively small part is mediated by weight (.701), and the remainder is not mediated by weight (2.161). (Because these are hypothetical data, this outcome does not accurately describe the importance of weight as a mediator in real-life situations.) The mediation analysis partitions the total effect of age on blood pressure ($c = 2.862$) into a direct effect ($c' = 2.161$) and a mediated effect ($ab = .701$). Within rounding error, $c = c' + ab$, that is, the total effect $c$ is the sum of the direct ($c'$) and mediated ($ab$) effects.

### 9.9 EVALUATING STATISTICAL SIGNIFICANCE

Several methods to test the statistical significance of mediated models have been proposed. The four most widely used procedures are briefly discussed: Baron and Kenny's (1986) causal-steps approach, joint significance tests for the $a$ and $b$ path coefficients, the Sobel test (Sobel, 1982) for $H_0: ab = 0$, and the use of bootstrapping to obtain confidence intervals (CIs) for the $ab$ product that represents the mediated or indirect effect.

#### 9.9.1 Causal-Steps Approach

Fritz and MacKinnon (2007) reviewed and evaluated numerous methods for testing whether mediation is statistically significant. A subset of these methods is described here.
Their review of mediation studies conducted between 2000 and 2003 revealed that the most frequently reported method was the causal-steps approach described by Baron and Kenny (1986). In Baron and Kenny's initial description of this approach, in order to conclude that mediation may be present, several conditions were required: first, a significant total relationship between $X_1$, the initial cause, and $Y$, the final outcome variable (i.e., a significant path $c$); significant $a$ and $b$ paths; and a significant $ab$ product using the Sobel test or a similar method, as described in Section 9.9.3. The decision of whether to call the outcome partial or complete mediation then depends on whether the $c'$ path that represents the direct path from $X_1$ to $Y$ is statistically significant; if $c'$ is not statistically significant, the result may be interpreted as complete mediation; if $c'$ is statistically significant, then only partial mediation may be occurring. Kenny has also noted elsewhere (http://www.davidakenny.net/cm/mediate.htm) that other factors, such as the sizes of coefficients and whether they are large enough to be of practical significance, should also be considered and that, as with any other regression analysis, meaningful results can be obtained only from a **correctly specified model**.

This approach is widely recognized, but it is not the most highly recommended procedure at present for two reasons. First, there are (relatively rare) cases in which mediation may occur even when the original $X_1$, $Y$ association is not significant. For example, if one of the paths in the mediation model is negative, a form of suppression may occur such that positive direct and negative indirect effects tend to cancel each other out to yield a small and non-significant total effect. (If $a$ is negative, while $b$ and $c'$ are positive, then when we combine a negative $ab$ product with a positive $c'$ coefficient to reconstitute the total effect $c$, the total effect $c$ can be quite small even if the separate positive direct path and negative indirect paths are quite large.) MacKinnon, Fairchild, and Fritz (2007) referred to this as **inconsistent mediation**; the mediator acts as a **suppressor variable**. See Chapter 3 for further discussion and an example of inconsistent mediation. Second, among the methods compared by Fritz and MacKinnon (2007), this approach had relatively low statistical power.

### 9.9.2 Joint Significance Test

Fritz and MacKinnon (2007) also discussed a joint significance test approach to testing the significance of mediation. The data analyst simply asks whether the $a$ and $b$ coefficients that constitute the mediated path are both statistically significant; the $t$ tests from the regression results are used. (On his mediation webpage at http://www.davidakenny.net/cm/mediate.htm, Kenny suggests that if this approach is used, and if an overall risk for Type I error of .05 is desired, each test should use $\alpha = .025$, two tailed, as the criterion for significance.) This approach is easy to implement and has moderately good statistical power compared with the other test procedures reviewed by Fritz and MacKinnon. However, it is not the most frequently reported method; journal reviewers may prefer better known procedures.

### 9.9.3 Sobel Test of $H_0: ab = 0$

Another method to assess the significance of mediation is to examine the product of the $a$, $b$ coefficients for the mediated path. (This is done as part of Baron and Kenny's [1986] causal-steps approach.) The null hypothesis, in this case, is $H_0: ab = 0$. To set up a $z$-test statistic, an estimate of the standard error of this $ab$ product ($SE_{ab}$) is needed. Sobel (1982) provided the following approximate estimate for $SE_{ab}$:

$$
SE_{ab} = \sqrt{\frac{b^2}{s^2_a} + \frac{a^2}{s^2_b}},
$$

(9.1)

where $a$ and $b$ are the raw (unstandardized) regression coefficients that represent the effect of $X_1$ on $X_2$ and the effect of $X_2$ on $Y$, respectively;
$s_a$ is the standard error of the $a$ regression coefficient; 
$s_b$ is the standard error of the $b$ regression coefficient.

Using the standard error from Equation 9.1 as the divisor, the following $z$ ratio for the Sobel test can be set up to test the null hypothesis $H_0$: $ab = 0$:

$$z = \frac{ab}{SE_{ab}}. \tag{9.2}$$

The $ab$ product is judged to be statistically significant if $z$ is greater than $+1.96$ or less than $-1.96$. This test is appropriate only for large sample sizes. The Sobel test is relatively conservative, and among the procedures reviewed by Fritz and MacKinnon (2007), it had moderately good statistical power. It is sometimes used in the context of Baron and Kenny's (1986) causal-steps procedure and sometimes reported without the other causal steps. The Sobel test can be done by hand; Preacher and Leonardelli (2008) provide an online calculator at http://quantpsy.org/sobel/sobel.htm to compute this $z$ test given either the unstandardized regression coefficients and their standard errors or the $t$ ratios for the $a$ and $b$ path coefficients. Their program also provides $z$ tests on the basis of alternative methods of estimating the standard error of $ab$ suggested by the Aroian test (Aroian, 1947) and Goodman test (Goodman, 1960).

The Sobel test was carried out for the hypothetical data on age, weight, and blood pressure. (Note again that the $N$ in this demonstration data set is too small for the Sobel test to yield accurate results; these data are used only to illustrate the use of the techniques.) For these hypothetical data, $a = 1.432, b = 0.490, s_a = 0.397$, and $s_b = 0.187$. These values were entered into the appropriate lines of the calculator provided at Preacher's webpage; the results appear in Figure 9.6. Because $z = 2.119$, with $p = .034$, two tailed, the $ab$ product that represents the effect of age on blood pressure mediated by weight can be judged statistically significant.

Note that the $z$ tests for the significance of $ab$ assume that values of this $ab$ product are normally distributed across samples from the same population; it has been demonstrated empirically that this assumption is incorrect for many values of $a$ and $b$. Because of this, authorities on mediation analysis (MacKinnon, Preacher, and their colleagues) now recommend bootstrapping methods to obtain CIs for estimates of $ab$.

### 9.9.4 Bootstrapped Confidence Interval for $ab$

Bootstrapping has become widely used in situations where the analytic formula for the standard error of a statistic is not known and/or there are violations of assumptions of normal distribution shape (Iacobucci, 2008). A sample is drawn from the population (with replacement), and values of $a$, $b$, and $ab$ are calculated for this sample. This process is repeated many times (bootstrapping procedures typically allow users to request from 1,000 up to 5,000 different samples). The value of $ab$ is tabulated across these samples; this provides an empirical sampling distribution that can be used to derive a value for the standard error of $ab$. Results of such bootstrapping indicate that the distribution of $ab$ values is often asymmetrical, and this asymmetry should be taken into account when setting up CI estimates of $ab$. This CI provides a basis for evaluation of the single estimate of $ab$ obtained from analysis of the entire data set. Bootstrapped CIs do not require that the $ab$ statistic have a normal distribution across samples. If this CI does not include zero, the analyst concludes that there is statistically significant mediation. Some bootstrapping programs include additional refinements, such as bias correction (see Fritz & MacKinnon, 2007). Most SEM programs, such as Amos, can provide bootstrapped CIs. A detailed example is presented in Chapter 15, on structural equation modeling.
Effect size information is usually given in unit-free form (Pearson’s $r$ and $r^2$ can both be interpreted as effect sizes). The raw or unstandardized path coefficients from mediation analysis can be converted to standardized slopes; alternatively, we can examine the correlation between $X_1$ and $X_2$ to obtain effect-size information for the $a$ path, as well as the partial correlation between $X_2$ and $Y$ (controlling for $X_1$) to obtain effect-size information for the $b$ path. There are potential problems with comparisons among standardized regression or path coefficients. For example, if the same mediation analysis involving the same set of three variables is conducted in two different samples (e.g., a sample of women and a sample of men), these samples may have different standard deviations on variables such as the predictor $X_1$ and the outcome variable $Y$. Suppose that the male and female samples yield $b$ and $c'$ coefficients that are very similar, suggesting that the amount of change in $Y$ as a function of $X_1$ is about the same across the two groups. When we convert raw-score slopes to standardized slopes, this may involve multiplying and dividing by different standard deviations for men and women, and different standard deviations within these groups could make it appear that the groups have different relationships between variables (different standardized slopes but similar unstandardized slopes).

Unfortunately, both raw score ($b$) and standardized ($\beta$) regression coefficients can be influenced by numerous sources of artifact that may operate differently in different groups. Appendix 10C in Volume I (Warner, 2020) reviewed numerous factors that can artifactually...
influence the size of *r* (such as outliers, curvilinearity, different distribution shapes for *X* and *Y*, unreliability of measurement of *X* and *Y*, etc.). Chapter 11 in Volume I demonstrated that β coefficients can be computed from bivariate correlations and that *b* coefficients are rescaled versions of β. When *Y* is the outcome and *X* is the predictor, \( b = \beta \times \left( \frac{SD_Y}{SD_X} \right) \). Both *b* and β coefficients can be influenced by many of the same problems as correlations. Therefore, if we try to compare regression coefficients across groups or samples, differences in regression coefficients across samples may be due partly to artifacts. Considerable caution is required whether we want to compare standardized or unstandardized coefficients.

Despite concerns about potential problems with standardized regression slopes (as discussed by Greenland et al., 1991), data analysts often include standardized path coefficients in reports of mediation analysis, particularly when some or all variables are not measured in meaningful units. In reporting results, authors should make it clear whether standardized or unstandardized path coefficients are reported. Given the difficulties just discussed, it is a good idea to include both types of path coefficients.

### 9.11 SAMPLE SIZE AND STATISTICAL POWER

Assuming the hypothesis of primary interest is \( H_0: \alpha \beta = 0 \), how large does sample size need to be to have an adequate level of statistical power? Answers to questions about sample size depend on several pieces of information: the alpha level, desired level of power, the type of test procedure, and the population effect sizes for the strength of the association between *X*₁ and *X*₂, as well as *X*₁ and *Y*. Often, information from past studies can help researchers make educated guesses about effect sizes for correlations between variables. In the discussion that follows, \( \alpha = 0.05 \) and desired power of 0.80 are assumed. We can use the correlation between *X*₁ and *X*₂ as an estimate of the effect-size index for *a* and the partial correlation between *X*₂ and *Y*, controlling for *X*₁, as an estimate of the effect size for *b*. On the basis of recommendations about verbal labels for effect size given by Cohen (1988), Fritz and MacKinnon (2007) designated a correlation of .14 as small, a correlation of .39 as medium, and a correlation of .59 as large. They reported statistical power for combinations of small (S), medium (M), and large (L) effect sizes for the *a* and *b* paths. For example, if a researcher plans to use the Sobel test and expects that both the *a* and *b* paths correspond to medium effects, the minimum recommended sample size from Table 9.1 would be 90.

A few cautions are in order: Sample sizes from this table may not be adequate to guarantee significance, even if the researcher has not been overly optimistic about anticipated effect size. Even when the power table suggests that fewer than 100 cases might be adequate for statistical power for the test of \( H_0: \alpha \beta = 0 \), analysts should keep in mind that small samples lead to more sampling error in estimates of path coefficients. For most studies that test mediation models, minimum sample sizes of 150 to 200 would be advisable if possible.

### 9.12 ADDITIONAL EXAMPLES OF MEDIATION MODELS

Several variations of the basic mediation model in Figure 9.1 are possible. For example, the effect of *X*₁ on *Y* could be mediated by multiple variables instead of just one (see Figure 9.7). Mediation could involve a multiple-step causal sequence. Mediation and moderation can both occur together. The following sections provide a brief introduction to each of these research situations; for more extensive discussion, see MacKinnon (2008).

#### 9.12.1 Multiple Mediating Variables

In many situations, the effect of a causal variable *X*₁ on an outcome *Y* might be mediated by more than one variable. Consider the effects of personality traits (such as extraversion
Table 9.1 Empirical Estimates of Sample Size Needed for Power of .80 When Using $\alpha = .05$ as the Criterion for Statistical Significance in Three Different Types of Mediation Analysis

<table>
<thead>
<tr>
<th>$ab$ Effect Size$^a$</th>
<th>Joint Significance$^b$</th>
<th>Sobel$^c$</th>
<th>Bootstrapped Confidence Interval$^d$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SS</td>
<td>530</td>
<td>667</td>
<td>558</td>
</tr>
<tr>
<td>SM</td>
<td>403</td>
<td>422</td>
<td>406</td>
</tr>
<tr>
<td>SL</td>
<td>403</td>
<td>412</td>
<td>398</td>
</tr>
<tr>
<td>MS</td>
<td>405</td>
<td>421</td>
<td>404</td>
</tr>
<tr>
<td>MM</td>
<td>74</td>
<td>90</td>
<td>78</td>
</tr>
<tr>
<td>ML</td>
<td>58</td>
<td>66</td>
<td>59</td>
</tr>
<tr>
<td>LS</td>
<td>405</td>
<td>410</td>
<td>401</td>
</tr>
<tr>
<td>LM</td>
<td>59</td>
<td>67</td>
<td>59</td>
</tr>
<tr>
<td>LL</td>
<td>36</td>
<td>42</td>
<td>36</td>
</tr>
</tbody>
</table>

Source: Adapted from Fritz and MacKinnon (2007, Table 3, p. 237).

Note: These power estimates may be inaccurate when measures of variables are unreliable, assumptions of normality are violated, or categorical variables are used rather than quantitative variables.

$^a$SS indicates that both $a$ and $b$ are small effects, SM indicates that $a$ is small and $b$ is medium, and SL indicates that $a$ is small and $b$ is large.

$^b$Joint significance test: Requirement that the $a$ and $b$ coefficients each are statistically significant.

$^c$A z test for $H_0: ab$ using a method to estimate $SE_{ab}$ proposed by Sobel (1982).

$^d$Without bias correction.

and neuroticism) on happiness. Extraversion is moderately positively correlated with happiness. Tkach and Lyubomirsky (2006) suggested that the effects of trait extraversion on happiness may be at least partially mediated by behaviors such as social activity. For example, people who score high on extraversion tend to engage in more social activities, and people who engage in more social activities tend to be happier. They demonstrated that, in their sample, the effects of extraversion on happiness were partially mediated by engaging in social activity, but there was still a significant direct effect of extraversion on happiness. Their mediation analyses examined only one behavior at a time as a potential mediator. Multiple mediators can easily be examined using SEM programs such as Amos, discussed later in this chapter.

9.12.2 Multiple-Step Mediated Paths

It is possible to examine a mediation sequence that involves more than one intermediate step, as in the sequence $X_1 \rightarrow X_2 \rightarrow X_3 \rightarrow Y$. If only partial mediation occurs, additional paths would need to be included in this type of model; for further discussion, see Taylor, MacKinnon, and Tein (2008).

9.12.3 Mediated Moderation and Moderated Mediation

It is possible for moderation (described in another chapter) to co-occur with mediation in two different ways. Mediated moderation occurs when two initial causal variables (let's
call these variables \( A \) and \( B \) have an interaction \((A \times B)\), and the effects of this interaction involve a mediating variable. In this situation, \( A \), \( B \), and the \( A \times B \) interaction are included as initial causal variables, and the mediation analysis is conducted to assess the degree to which a potential mediating variable explains the impact of the \( A \times B \) interaction on the outcome variable. The PROCESS macros provided by Andrew Hayes (2017, 2019) are extremely useful for assessment of models with moderated mediation, or mediated moderation.

Moderated mediation occurs when you have two different groups (e.g., men and women), and the strength or signs of the paths in a mediation model for the same set of variables differ across these two groups. Many SEM programs, such as Amos, make it possible to compare path models across groups and to test hypotheses about whether one, or several, path coefficients differ between groups (e.g., men vs. women). Further discussion can be found in

Source: Adapted from Warner and Vroman (2011).
Note: Coefficient estimates and statistical significance tests were obtained using the Indirect.sps script (output not shown). The effect of extraversion on happiness was partially mediated by behaviors. Positive/proactive behaviors \((a_1 \times b_1)\) and health behaviors \((a_3 \times b_3)\) were significant mediators; spiritual behaviors did not significantly mediate effects of extraversion on happiness.

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**Figure 9.7** Path Model for Multiple Mediating Variables Showing Standardized Path Coefficients

![Path Model Diagram]

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Edwards and Lambert (2007); Muller, Judd, and Yzerbyt (2005); and Preacher, Rucker, and Hayes (2007). Comparison of models across groups using the Amos SEM program was demonstrated by Byrne (2016).

9.13 NOTE ABOUT USE OF STRUCTURAL EQUATION MODELING PROGRAMS TO TEST MEDIATION MODELS

SEM programs such as LISREL, EQS, Mplus, and Amos make it possible to test models that include multiple-step paths (e.g., mediation hypotheses) and to compare results across groups (to test moderation hypotheses). In addition, SEM programs make it possible to include multiple indicator variables for some or all of the constructs; in theory, this makes it possible to assess multiple indicator measurement reliability. Most SEM programs now also provide bootstrapping; most analysts now view SEM programs as the preferred method for assessment of mediated models. More extensive discussion of other types of analyses that can be performed using SEM is beyond the scope of this book; for further information, see Byrne (2009) or Kline (2016).

There are two reasons why it is worthwhile to learn how to use Amos (or other SEM programs) to test mediated models. First, it is now generally agreed that bootstrapping is the preferred method to test the statistical significance of indirect effects in mediated models; bootstrapping may be more robust to violations of assumptions of normality. Second, once a student has learned to use Amos (or other SEM programs) to test simple mediation models similar to the example in this chapter, the program can be used to add additional predictor and/or mediator variables, as shown in Figure 9.11.

9.14 RESULTS SECTION

For the hypothetical data in this chapter, a “Results” section could read as follows. Results presented here are based on the output from linear regression (Figures 9.2–9.4) and the Sobel test result in Figure 9.6. (Results would include slightly different numerical values if the Amos output is used.)

Results

A mediation analysis was performed using Baron and Kenny’s (1986) causal-steps approach; in addition, a bootstrapped CI for the ab indirect effect was obtained using procedures described by Preacher and Hayes (2008). The initial causal variable was age, in years; the outcome variable was systolic blood pressure (SBP), in millimeters of mercury; and the proposed mediating variable was body weight, in pounds. [Note: The sample N, mean, standard deviation, minimum and maximum scores for each variable, and correlations among all three variables would generally appear in earlier sections.] Refer to Figure 9.1 for the path diagram that corresponds to this mediation hypothesis. Preliminary data screening suggested that there were no serious violations of assumptions of normality or linearity. All coefficients reported here are unstandardized, unless otherwise noted; α = .05, two tailed, is the criterion for statistical significance.

The total effect of age on SBP was significant, $c = 2.862$, $t(28) = 6.631$, $p < .001$; each 1-year increase in age predicted approximately a 3-point increase in SBP. Age was significantly predictive of the hypothesized mediating variable, weight; $a = 1.432$, $t(28) = 3.605$, $p = .001$. When controlling for age, weight was significantly predictive
of SBP, \( b = .490, t(27) = 2.623, p = .014 \). The estimated direct effect of age on SBP, controlling for weight, was \( \hat{c}' = 2.161, t(27) = 4.551, p < .001 \).

SBP was predicted quite well from age and weight, with adjusted \( R^2 = .667 \) and \( F(2, 27) = 30.039, p < .001 \).

The indirect effect, \( ab \), was .701. This was judged to be statistically significant using the Sobel test, \( z = 2.119, p = .034 \). [Note: The Sobel test should be used only with much larger sample sizes than the \( N \) of 30 for this hypothetical data set.] Using the SPSS script for the indirect procedure (Preacher & Hayes, 2008), bootstrapping was performed; 5,000 samples were requested; a bias-corrected and accelerated CI was created for \( ab \). For this 95% CI, the lower limit was .0769 and the upper limit was 2.0792.

Several criteria can be used to judge the significance of the indirect path. In this case, both the \( a \) and \( b \) coefficients were statistically significant, the Sobel test for the \( ab \) product was significant, and the bootstrapped CI for \( ab \) did not include zero. By all these criteria, the indirect effect of age on SBP through weight was statistically significant. The direct path from age to SBP (\( \hat{c}' \)) was also statistically significant; therefore, the effects of age on SBP were only partly mediated by weight.

The upper diagram in Figure 9.5 shows the unstandardized path coefficients for this mediation analysis; the lower diagram shows the corresponding standardized path coefficients.

Comparison of the coefficients for the direct versus indirect paths (\( \hat{c}' = 2.161 \) vs. \( ab = .701 \)) suggests that a relatively small part of the effect of age on SBP is mediated by weight. There may be other mediating variables through which age might influence SBP, such as other age-related disease processes.

### 9.15 SUMMARY

This chapter demonstrates how to assess whether a proposed mediating variable (\( X_2 \)) may partly or completely mediate the effect of an initial causal variable (\( X_1 \)) on an outcome variable (\( Y \)). The analysis partitions the total effect of \( X_1 \) on \( Y \) into a direct effect, as well as an indirect effect through the \( X_2 \) mediating variable. The path model represents causal hypotheses, but readers should remember that the analysis cannot prove causality if the data are collected in the context of a nonexperimental design. If controlling for \( X_2 \) completely accounts for the correlation between \( X_1 \) and \( Y \), this could happen for reasons that have nothing to do with mediated causality; for example, this can occur when \( X_1 \) and \( X_2 \) are highly correlated with each other because they measure the same construct. A mediation analysis should be undertaken only when there are good reasons to believe that \( X_1 \) causes \( X_2 \) and that \( X_2 \) in turn causes \( Y \). In addition, it is highly desirable to collect data in a manner that ensures temporal precedence (i.e., \( X_1 \) occurs first, \( X_2 \) occurs second, and \( Y \) occurs third).

These analyses can be done using OLS regression; however, use of SPSS scripts provided by Preacher and Hayes (2008) provides bootstrapped estimates of CIs, and most analysts now believe this provides better information than statistical significance tests that assume normality. SEM programs provide even more flexibility for assessment of more complex models.

If a mediation analysis suggests that partial or complete mediation may be present, additional research is needed to establish whether this is replicable and real. If it is possible to manipulate or block the effect of the proposed mediating variable experimentally, experimental work can provide stronger evidence of causality (MacKinnon, 2008).
COMPREHENSION QUESTIONS

1. Suppose that a researcher first measures a Y outcome variable, then measures an X₁ predictor and an X₂ hypothesized mediating variable. Why would this not be a good way to collect data to test the hypothesis that the effects of X₁ on Y may be mediated by X₂?

2. Suppose a researcher wants to test a mediation model that says that the effects of math ability (X₁) on science achievement (Y) are mediated by sex (X₂). Is this a reasonable mediation hypothesis? Why or why not?

3. A researcher believes that the prediction of Y (job achievement) from X₁ (need for power) is different for men versus women (X₂). Would a mediation analysis be appropriate? If not, what other analysis would be more appropriate in this situation?

4. Refer to Figure 9.1. If a, b, and ab are all statistically significant (and large enough to be of practical or clinical importance), and c’ is not statistically significant and/or not large enough to be judged practically or clinically important, would you say that the effects of X₁ on Y are partially or completely mediated by X₂?

5. What pattern of outcomes would you expect to see for coefficient estimates in Figure 9.1; for example, which coefficients would need to be statistically significant and large enough to be of practical importance, for the interpretation that X₁ only partly mediates the effects of X₁ on Y? Which coefficients (if any) should be not statistically significant if the effect of X₁ on Y is only partly mediated by X₂?

6. In Figure 9.1, suppose that you initially find that path c (the total effect of X₁ on Y) is not statistically significant and too small to be of any practical or clinical importance. Does it follow that there cannot possibly be any indirect effects of X₁ on Y that are statistically significant? Why or why not?

7. Using Figure 9.1 again, consider this equation: c = (a × b) + c’. Which coefficients represent direct, indirect, and total effects of X₁ on Y in this equation?

8. A researcher believes that the a path in a mediated model (see Figure 9.1) corresponds to a medium unit-free effect size and the b path in a mediated model also corresponds to a medium unit-free effect size. If assumptions are met (e.g., scores on all variables are quantitative and normally distributed), and the researcher wants to have power of about .80, what sample size would be needed for the Sobel test (according to Table 9.1)?

9. Give an example of a three-variable study for which a mediation analysis would make sense. Be sure to make it clear which variable is the proposed initial predictor, mediator, and outcome.

10. Briefly comment on the difference between the use of a bootstrapped CI (for the unstandardized estimate of ab) versus the use of the Sobel test. What programs can be used to obtain the estimates for each case? Which approach is less dependent on assumptions of normality?

NOTES

¹For discussion of potential problems with comparisons among standardized regression coefficients, see Greenland, Maclure, Schlesselman, Poole, and Morgenstern (1991). Despite the problems they and others have identified, research reports still commonly report standardized
regression or path coefficients, particularly in situations where variables have arbitrary units of measurement.

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