this kind of test says that the population value of the beta weight is 0. Stated differently, the null hypothesis in such tests is that the regression line has no tilt, thus meaning that the independent variable provides no assistance in predicting scores on the dependent variable.

Multiple Regression

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Multiple regression

We now turn our attention to the most popular regression procedure of all, **multiple regression.** This form of regression involves, like bivariate regression, a single dependent variable. In multiple regression, however, there are two or more independent variables. Stated differently, multiple regression involves just one Y variable but two, three, or more X variables.[5]

In three important respects, multiple regression is identical to bivariate regression. First, a researcher's reason for using multiple regression is the same as the reason for using bivariate regression, either prediction (with a focus on the dependent variable) or explanation (with a focus on the independent variables). Second, a regression equation is involved in both of these regression procedures. Third, both bivariate and multiple regression almost always involve inferential tests and a measure of the extent to which variability among the scores on the dependent variable has been explained or accounted for.

Though multiple regression and bivariate regression are identical in some respects, they also differ in three extremely important ways. As you will see, multiple regression can be done in *different ways* that lead to different results, it can be set up to accommodate *covariates* that the researcher wishes to control, and it can involve (as predictor variables) one or more *interactions* between independent variables. Bivariate regression has none of these characteristics.

In upcoming sections, these three unique features of multiple regression will be discussed. We begin, however, with a consideration of the regression equation that comes from the analysis of data on one dependent variable and multiple independent variables. This equation functions as the most important stepping stone between the raw scores collected in a study and the findings extracted from the investigation.

The Regression Equation

When a regression analysis involves one dependent variable and two independent variables, the regression equation takes the form

$$Y' = a + b_1 \cdot X_1 + b_2 \cdot X_2$$

[5]Recall that the dependent variable (Y) is sometimes referred to as the criterion, outcome, or response variable while the independent variable (X) is sometimes referred to as the predictor or explanatory variable.

where Y' stands for the predicted score on the dependent variable, a stands for the constant, b_1 and b_2 are regression coefficients, and X_1 and X_2 represent the two independent variables. In Excerpt 16.11, we see a regression equation that has this exact form.

EXCERPT 16.11 • *A Regression Equation for the Case of Two Independent Variables*

The regression formula predicting overweight reduction was:

$$Y = 6.34 + 7.06X_1 = 4.17X_2$$

where X_1 is the change in eating between meals and X_2 is the change in eating while doing another activity.

Source: Golan, M., Fainaru, M., and Weizman, A. (1998). Role of behaviour modification in the treatment of childhood obesity with the parents as the exclusive agents of change. *International Journal of Obesity, 22,* p. 1221.

As indicated previously, multiple regression can accommodate more than two independent variables. In such cases, the regression equation will simply be extended to the right, with an extra term (made up of a new b multiplied by the new X) added for each additional independent variable. The presence of these extra terms, of course, does not alter the fact that the regression equation contains only one Y' term (located on the left side of the equation) and only one a term (located on the right side of the equation).

Excerpt 16.12 illustrates what a multiple regression equation looks like when more than two independent variables are involved in the analysis. In the study

EXCERPT 16.12 • *Regression Equation with Several Independent Variables*

In the first regression analysis, the predictor variables were the four attitude variables—*Enjoyment* (X_1), *Motivation* (X_2), *Importance* (X_3), and *Freedom from Anxiety* (X_4); and the response variable was *Time* (Y)—time spent on learning or using technologies. . . . The regression analysis generated a set of coefficients that were used to formulate the regression equation:

$$Y = -428.15 + 15.22\,(X_1) + 3.34(X_2) + 16.02(X_3) + 5.57\,(X_4)$$

Source: Liu, L., Maddux, C., and Johnson, L. (2004). Computer attitude and achievement: Is time an intermediate variable? *Journal of Technology and Teacher Education, 12*(4), pp. 599, 600.

associated with this excerpt, the researchers collected data from 609 college students enrolled in a three-semester computer technology course. To answer one of their questions, the researchers used a multiple regression analysis to see if certain attitudinal variables could predict how much time the students spent outside of class trying to improve their technology skills. In Excerpt 16.12, the researchers clarify which four attitudes were used as independent (i.e., predictor) variables. Note that the researchers refer to the dependent variable as the **response variable.**

In each of the regression equations shown in Excerpts 16.11 and 16.12, the algebraic sign between any two adjacent terms on the right side of the equation is positive. This means that the sign of every regression coefficient was positive. In some multiple regression equations, one of more of the *b*s will end up being negative. The sign of a regression coefficient simply indicates the nature of the relationship between that particular *X* variable and the dependent variable. Thus, if the students in the study that gave us Excerpt 16.12 had also been measured on how extensively they were involved in extracurricular activities, I would expect this predictor variable's regression coefficient to have a negative sign in front of it, thereby implying an inverse relationship between involvement in extracurricular activities and time spent on the computer.

Regardless of whether the multiple regression is being conducted for predictive or explanatory purposes, the researcher is usually interested in comparing the independent variables to see the extent to which each one helps the regression analysis achieve its objective. In other words, there is usually interest in finding out the degree to which each independent variable contributes to successful predictions or valid explanations. Although you (as well as a fair number of researchers) may be tempted to look at the *b*s in order to find out how well each independent variable works, this should not be done because each regression coefficient is presented in the units of measurement used to measure its corresponding *X*. Thus if one of the independent variables in a multiple regression is height, its *b* will differ in size depending on whether height measurements are made in centimeters, inches, feet, or miles.

To determine the relative importance of the different independent variables, the researcher needs to look at something other than an **unstandardized regression equation** like those we have seen thus far. Instead, a **standardized regression equation** can be examined. This kind of regression equation, for the case of three independent variables, would take the form

$$z'_y = \beta_1 \cdot z_{x1} + \beta_2 \cdot z_{x2} + \beta_3 \cdot z_{x3}.$$

As you will note, this equation presents the dependent and independent variables in terms of *z*, it has no constant term, and it uses the symbol β instead of *b*. These βs are like standardized regression coefficients, and they are called **beta weights.**

Although standardized regression equations are rarely included in research reports, researchers often extract the beta weights from such equations and present the numerical values of these βs. In Excerpts 16.13 and 16.14, we see two instances in which this was done. Notice that the beta weights are referred to as "beta" in the first of these excerpts, while the symbol β is used in the second excerpt.

Before concluding our discussion of regression equations, three important points need to be made. First, one or more of the independent variables in a regression analysis can be categorical in nature. For example, gender is often used in multiple regression to help accomplish the researcher's predictive or explanatory objectives. As you see the technique of multiple regression used in different studies, you are likely to see a wide variety of categorical independent variables included, such as marital status (single, married, divorced), highest educational degree (H.S. diploma, bachelor's degree, Master's degree, Ph.D.), and race (Black, White, Hispanic).

Second, researchers often include a term in the regression equation that represents the interaction between two of the study's independent variables. In Excerpt 16.15, we see such a case.

Researchers use interaction terms in multiple regression analyses for many different reasons. At times, the researcher is simply interesting in having R^2 be as large as possible. Putting an interaction term into the regression equation as a new independent variable may lead to an increase in the predictability of the dependent variable. Though this is done on occasion, most researchers use interactions in their regression analyses for a different reason.

EXCERPTS 16.13–16.14 • *Beta Weights*

This study examined the relationship between student performance on collaborative learning group assignments and students' examination scores in statistics. . . . A multiple regression technique was used to analyze the data. . . . As revealed by a comparison of the standardized regression coefficients, group project 2 (*Beta* = .205) exerted an effect on final examination scores that was less than half that for the mean quiz score (*Beta* = .564).

Source: Delucchi, M. (2006). The efficacy of collaborative learning groups in an undergraduate statistics course. *College Teaching, 54*(2), pp. 244, 246.

We used a standard multiple regression analysis to test the efficacy of the original TPB variables and self-efficacy in predicting residents' intentions to follow the rules at youth shelters. . . . Two of the variables were significant predictors of intention. Self-efficacy, $\beta = .47$, emerged as the strongest predictor of intention to follow the shelter rules; and subjective norm, $\beta = .34$, emerged as another such significant predictor.

Source: Broadhead-Fearn, D., and White, K. M. (2006). The role of self-efficacy in predicting rule-following behaviors in shelters for homeless youth: A test of the theory of planned behavior. *Journal of Social Psychology, 146*(3), p. 316.

EXCERPT 16.15 • *Interactions as Independent Variables*

In the first set of analyses, two multiple regression equations were created, and in both equations the criterion variable was customer satisfaction. With the first regression equation (the full equation), the predictor variables were provider occupation type (effect coded), courteous expressions, and an interaction term created by multiplying courteous expressions by service provider occupational level.

Source: Koermer, C. D. (2005). Service provider type as a predictor of the relationship between sociality and customer satisfaction. *Journal of Business Communication, 42*(3), p. 254.

The inclusion of an interaction term creates a situation in which the researcher can see if the regression equation works similarly for different levels of the variables involved in the interaction. Consider again Excerpt 16.15. In that study, the researcher could have conducted a simple bivariate regression to see if courteous expressions (from workers) predict customer satisfaction. By including service provider type as a second independent variable and the interaction (of service provider type with courteous expressions), the researcher had a chance to see whether the degree of association between courteous expressions and customer service varied across different types of service provider businesses. If so, then type of service provider could be called a **moderator variable.** Just as an interaction in a two-way ANOVA asks whether the main effect means of one of the factors describe well that factor's simple main effect means (at different levels of the other factor), an interaction term in a regression analysis asks whether the equation predicting the dependent variable stays the same for different categories of one of the variables involved in the interaction.

My third and final comment about regression equations is an important warning. Simply stated, be aware that the regression coefficients (or beta weights) associated with the independent variables can change dramatically if the analysis is repeated with one of the independent variables discarded or another independent variable added. Thus regression coefficients (or beta weights) do not provide a pure and absolute assessment of any independent variable's worth. Instead, they are "context dependent."

Three Kinds of Multiple Regression

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Simultaneous multiple regression

Different kinds of multiple regression exist because there are different orders in which data on the independent variables can be entered into the analysis. In this section, we will consider the three most popular versions of multiple regression. These are called simultaneous multiple regression, stepwise multiple regression, and hierarchical multiple regression.

In **simultaneous multiple regression,** the data associated with all independent variables are considered at the same time. This kind of multiple regression is analogous to the process used in preparing vegetable soup where all ingredients are thrown into the pot at the same time, stirred, and then cooked together. In Excerpt 16.16, we see an example of simultaneous multiple regression.

EXCERPT 16.16 • *Simultaneous Multiple Regression*

Simultaneous multiple regression analyses were conducted to further examine the extent to which Sport MPS subscales related in theoretically meaningful ways to Hewitt-MPS subscales. Each Sport-MPS subscale was separately entered as the dependent variable in regression analyses, with the three Hewitt MPS subscales simultaneously entered as the independent (or predictor) variables.

Source: Dunn, J. G. H., Dunn, J. C., Gotwals, J. K., Vallance, J. K. H., Craft, J. M., and Syrotuik, D. G. (2006). Establishing construct validity evidence for the Sport Multidimensional Perfectionism Scale. *Psychology of Sport & Exercise, 7*(1), p. 68.

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Stepwise multiple regression

The second kind of multiple regression analysis is analogous to the process of preparing a soup in which the ingredients are tossed into the pot based on the amount of each ingredient. Here the stock goes in first (because there's more of that than anything else), followed by the vegetables, the meat, and finally the seasoning. Each of these different ingredients is meant to represent an independent variable, with "amount of ingredient" equated to the size of the bivariate correlation between a given independent variable and the dependent variable. Here, in **stepwise multiple regression,** the computer determines the order in which the independent variables become a part of the regression equation. In Excerpt 16.17, we see an example of this kind of multiple regression.

Instead of preparing our vegetable soup by simply tossing everything into the pot at once or by letting the amount of an ingredient dictate its order of entry, we

EXCERPT 16.17 • *Stepwise Multiple Regression*

To determine factors affecting academic performance as assessed by average mark at the end of the first year, stepwise multiple regression was first carried out with average mark as the dependent variable to discover which variables were related to academic performance. The following independent variables were entered: age category at entry (under 21, 21 to 25, over 25), gender, socio-economic class, A-Level points, father with/without degree, mother with/without degree, three life goal scores, three study approaches.

Source: Wilding, J., and Andrews, B. (2006). Life goals, approaches to study and performance in an undergraduate cohort. *British Journal of Educational Psychology, 76*(1), p. 177.

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Hierarchical multiple regression

could put things into the pot on the basis of concerns regarding flavor and tenderness. If we wanted garlic to flavor everything else, we'd put it in first even though there's only a small amount of it required by the recipe. Similarly, we would hold back some of the vegetables (and not put them in with the others) if they are tender to begin with and we want to avoid overcooking them. **Hierarchical multiple regression** is like cooking the soup in this manner, for in this form of regression the independent variables are entered into the analysis in stages. Often, as illustrated in Excerpt 16.18, the independent variables that are entered first correspond with things the researcher wishes to control. After they are allowed to explain as much variability in the dependent variable as they can, then the other variables are entered to see if they can contribute above and beyond the independent variables that went in first.

EXCERPT 16.18 • *Hierarchical Multiple Regression*

A hierarchical linear regression analysis was used to predict intention to engage in a binge drinking session over the next week. The independent variables were entered in three blocks: (i) age and gender, (ii) attitude, subjective norm, self-efficacy, and perceived control, and (iii) past binge drinking. In this way, it was possible to examine the predictive utility of the TPB [theory of planned behaviour] variables, controlling for the effects of age and gender, as well as the additional predictive utility of past behaviour.

Source: Norman, P. and Conner, M. (2006). The theory of planned behaviour and binge drinking: Assessing the moderating role of past behaviour within the theory of planned behaviour. *British Journal of Health Psychology, 11*(1), p. 60.

R, R^2, ΔR^2, and Adjusted R^2 in Multiple Regression

In multiple regression studies, the extent to which the regression analysis achieves its objective is usually quantified by means of R, R^2, or adjusted R^2. Sometimes two of these will be presented, and occasionally you will see all three reported for the same regression analysis. These elements of a multiple regression analysis are not superficial and optional add-ons; instead, they are as central to a regression analysis as the regression equation itself.

In bivariate regression, r provides an indication of how well the regression equation works. It does that by quantifying the degree to which the predicted scores match up with the actual scores (on the dependent variable) for the group of individuals used to develop the regression equation. The R of multiple regression can be interpreted in precisely the same way. **Multiple *R*** is what we would get if we computed Pearson's r between Y and Y' scores for the individuals who provided scores on the independent and dependent variables.

Although the value of R sometimes appears when the results of a multiple regression are reported, researchers are far more likely to report the value of R^2 or to report the percentage equivalent of R^2. By so doing, the success of the regression analysis is quantified by reporting the proportion or percentage of the variability in the dependent variable that has been accounted for or explained by the study's independent variables. Excerpt 16.19 illustrates the way researchers use R^2 in an explained variance manner.

EXCERPT 16.19 • *R^2 as an Index of Explained Variance*

A multiple regression analysis was conducted to determine predictors of meeting length. The predictors were student age, student grade, and number of participants at the meeting. . . . The sample multiple correlation coefficient was .52, indicating that approximately 27% of the variance of length of meeting can be accounted for by the linear combination of these variables.

Source: Martin, J. E., Van Dycke, J. L., Greene, B. A., Gardner, J. E., Christensen, W. R., Woods, L. L., and Lovett, D. L. (2006). Direct observation of teacher-directed IEP meetings: Establishing the need for student IEP meeting instruction. *Exceptional Children, 72*(2), p. 195.

When a multiple regression analysis is conducted with the data from all independent variables considered simultaneously, only one R^2 can be computed. In stepwise and hierarchical regression, however, several R^2 values can be computed, one for each stage of the analysis wherein individual independent variables or sets of independent variables are added. These R^2 values will get larger at each stage, and the increase from stage to stage is referred to as **R^2 change.** Another label for the increment in R^2 that's observed as more and more independent variables are used as predictors is **ΔR^2,** where the symbol Δ stands for the two-word phrase "change in."

Excerpt 16.20 illustrates nicely the concept of ΔR^2. In the first step of the hierarchical multiple regression, three "control" variables were used to predict the dependent variable, student evaluation of the course. Those variables produced a very small R^2. Next, in the second step of the regression analysis, three additional independent variables entered the model and caused R^2 to change from .044 to .504. Thus, the increase in R^2 (i.e., ΔR^2) was equal to .46. At the end of the second step, with the regression model using all six independent variables, 50.4 percent of the variability in the students' course evaluations was explained by the full set of independent variables.

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Adjusted R^2

Either in place of or in addition to R^2, something called **adjusted R^2** is often reported in conjunction with a multiple regression analysis. If reported, adjusted R^2 will take the form of a proportion or a percentage. It is interpreted just like R^2, because it indicates the degree to which variability in the dependent variable is explained by the set of independent variables included in the analysis. The conceptual difference between R^2 and adjusted R^2 is related to the fact that the former,

EXCERPT 16.20 • ΔR^2 *in Stepwise or Hierarchical Multiple Regression*

We performed a hierarchical multiple regression analysis with student evaluations of course outcomes as the dependent variable. Variables entered the equation in two steps. First, the control variables of students' self-reported achievement (i.e., students reported their grade point average), dummy coded instructor, and student gender entered the equation. Results showed that the squared multiple correlation for this equation was [equal to] $R^2 = .044$. . . . Second, the predictor variables of course expectations, affective journal outcomes, and cognitive journal outcomes entered the equation. Results showed that the change in the squared multiple correlation for this equation was [equal to] $\Delta R^2 = .46$. . . . Overall, the [full] regression equation explained just over 50% of the variance. . . .

Source: Bolin, A. U., Khramtsova, I., and Saarnio, D. (2005). Using student journals to stimulate authentic learning: Balancing Bloom's cognitive and affective domains. *Teaching of Psychology, 32*(3), p. 157.

being based on sample data, always yields an overestimate of the corresponding population value of R^2.

Adjusted R^2 removes the bias associated with R^2 by reducing its value. Thus this adjustment anticipates the amount of so-called **shrinkage** that would be observed if the study were to be replicated with a much larger sample. As you would expect, the size of this adjustment is inversely related to study's sample size.[6]

When reporting the results of their multiple regression analyses, some researchers (who probably do not realize that R^2 provides an exaggerated index of predictive success) report just R^2. Of those who are aware of the positive bias associated with R^2, some will include only adjusted R^2 in their reports while others will include both R^2 and adjusted R^2. In Excerpt 16.21, we see an example of the latter situation.

EXCERPT 16.21 • *Adjusted* R^2

A hierarchical regression model was used to explore the relationship of predictor variables to the criterion variable. . . . The contribution of age and education was significant, $R^2 = .19$, adjusted $R^2 = .18, p < .001$. ATG-S explained significant additional variance, 14%, in the second step, $R^2 = .33$, adjusted $R^2 = .32, p < .001$. In the final step, the block of GRCS-I variables accounted for 4% of additional variance ($R^2 = .38$, adjusted $R^2 = .35, p < .01$).

Source: Kassing, L. R., Beesley, D., and Frey, L. L. (2005). Gender role conflict, homophobia, age, and education as predictors of male rape myth acceptance. *Journal of Mental Health Counseling, 27*(4), p. 321.

[6]The size of the adjustment is also influenced by the number of independent variables. With more independent variables, the adjustment is larger.

Inferential Tests in Multiple Regression

Researchers can apply several different kinds of inferential tests when they perform a multiple regression. The three most frequently seen tests focus on β, R^2, and ΔR^2. Let's consider what each of these tests does and then we will look at an excerpt in which all three of these tests were used.

When the beta weight for a particular independent variable is tested, the null hypothesis says that the parameter value is equal to 0. If this were true, that particular independent variable would be contributing nothing to the predictive or explanatory objective of the multiple regression. Because of this, researchers frequently will test each of the betas in an effort to decide (1) which independent variables should be included in the regression equation that is in the process of being built or (2) which independent variables included in an already-developed regression equation turned out to be helpful. Beta weights are normally tested with two-tailed *t*-tests.[7]

When R^2 is tested, the null hypothesis says that none of the variance in the dependent variable is explained by the collection of independent variables. (This H_0, of course, has reference to the study's population, not its sample.) This null hypothesis normally is evaluated via an *F*-test. In most studies, the researcher will be hoping that this H_0 will be rejected.[8]

When ΔR^2 is tested, the null hypothesis says that the new independent variable(s) added to the regression equation is totally worthless in helping to explain variability in the dependent variable. As with the null hypotheses associated with tests on beta weights and R^2, this particular H_0 has reference to the study's population, not its sample. A special *F*-test is used to evaluate this null hypothesis. This kind of test, of course, logically fits into the procedures of stepwise and hierarchical multiple regression; it would never be used within the context of a simultaneous multiple regression.[9]

Consider now Excerpt 16.22 which comes from a study involving a hierarchical multiple regression. Take the time to look at this excerpt closely. As you will see, it contains tests of beta weights, a test of R^2 at the first step of the analysis, a test of the incremental R^2 as the analysis moved from the first to the second step, and a test of R^2 for the full model as explicated in step 2.

Two additional features of Excerpt 16.22 are noteworthy. First, the size of the beta weights associated with the therapists' level and experience of self-awareness changed as the analysis moved from step 1 to step 2. (In step 1, therapist level of self-awareness was significant at $p \leq .05$; in step 2, that same independent variable was significant at $p \leq .01$.). Such a change in the assessed value of an independent

[7]The *df* for this kind of *t*-test is equal to the sample size minus one more than the number of independent variables.

[8]The first *df* for this kind of *F*-test is equal to the number of independent variables; the second *df* value is equal to the sample size minus one more than the number of independent variables.

[9]The *df* for this kind of *F*-test is equal to (a) the number of new independent variables and (b) the sample size minus one more than the total number of old and new independent variables.

EXCERPT 16.22 • *Inferential Tests in Multiple Regression*

TABLE 1 ***Hierarchical Multiple Regression Results for Clients' Perception of the Therapy Session Regressed onto Therapists' Level, Experience, and Management of In-Session Self-Awareness***

Criterion variable: SIS Relationship Impact scores	***B***	***SE B***	***β***
Step 1: *df* = 2, 14			
Therapist level of self-awareness	1.66	0.74	0.58*
Therapist experience of self-awareness	−0.17	1.19	−0.04
Step 2: *df* = 3, 13			
Therapist level of self-awareness	2.96	0.89	1.04**
Therapist experience of self-awareness	−0.67	1.08	−0.15
Therapist management strategies	−13.87	6.37	−0.59*

Note: $R^2 = .32$ for Step 1 ($p > .05$); $\Delta R^2 = .18$ for Step 2 ($p \leq .10$); $R^2 = .50$ for Step 2 ($p \leq .05$) for the full model. SIS = Session Impacts Scale.

*$p \leq .05$. **$p \leq .01$.

Source: Fauth, J., and Williams, E. N. (2005). The in-session self-awareness of therapist-trainees: Hindering or helpful? *Journal of Counseling Psychology, 52*(3), p. 445.

variable is not uncommon in stepwise and multiple regression. Hence, the hierarchical value of any independent variable is not absolute; rather, its usefulness depends upon the context (i.e., whether other independent variables are also involved in the multiple regression and, if there are other predictor variables, what kinds of relationships exist among the independent and dependent variables).

The second thing to notice about Excerpt 16.22 is the fact that the value of R^2 increased from step 1 to step 2, and it changed from being "$p > .05$" to being "$p \leq .05$." This shows that the independent variable that was added into the model at step 2 made a difference. Apart from just noting that the first R^2 was *not* significant whereas the second R^2 *was* significant, note that the estimated level of explained variance increased from 32 percent to 50 percent.

Logistic Regression

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Logistic regression

The final kind of regression considered in this chapter is called logistic regression. Originally, only researchers from medical disciplines (especially epidemiology) used this form of regression. More recently, however, **logistic regression** has been discovered by those who conduct empirical investigations in other disciplines. Its popularity continues to grow at such a rate that it may soon overtake multiple regression and become the most frequently used regression tool of all.

Before considering how logistic regression differs from the forms of regression already considered, let's look at their similarities. First, logistic regression deals with relationships among variables (not mean differences), with one variable being the dependent (i.e., outcome or response) variable while the other(s) is/are the independent (predictor or explanatory) variable(s). Second, the independent variables can be continuous or categorical in nature. Third, the purpose of logistic regression can be either prediction or explanation. Fourth, tests of significance can be and usually are conducted, with these tests targeted either at each individual independent variable or at the combined effectiveness of the independent variables. Finally, logistic regression can be conducted in a simultaneous, stepwise, or hierarchical manner dependent on the timing of and reasons for independent variables entering the equation.

There are, of course, important differences between logistic regression, on the one hand, and either bivariate or multiple regression, on the other hand. These differences will be made clear in the next three sections. As you will see, logistic regression revolves around a core concept called the **odds ratio** that was not considered earlier in the chapter because it is not a feature of either bivariate or multiple regression. Before looking at this new concept, we need to focus our attention on the kinds of data that go into a logistic regression and also the general reasons for using this kind of statistical tool.

Variables

As does any bivariate or multiple regression, logistic regression always involves two main kinds of variables. These are the study's *dependent* and *independent* variables. In the typical logistic regression (as in some applications of multiple regression), a subset of the independent variables is included for control purposes, with the label *control* (or *covariate*) designating any such variable. Data on these three variables constitute the only ingredients that go into the normal logistic regression, and the results of such analyses are inextricably tied, on a conceptual level, to these three kinds of variables. For these reasons, it is important for us to begin with a careful consideration of the logistic regression's constituent parts.

In any logistic regression, as in any bivariate or multiple regression, there is one and only one dependent variable. Here, however, the dependent variable is dichotomous (i.e., binary) in nature. Examples of such variables used in recent studies include whether or not a person survives open heart surgery, whether or not an elderly and ill married person considers his/her spouse to be the primary caregiver, whether or not a young child chronically suffers from nightly episodes of coughing, and whether or not an adolescent drinks at least eight ounces of milk a day. As illustrated by these examples, the dependent variable in a logistic regression can represent either a true dichotomy or an artificial dichotomy.

In addition to the dependent variable, at least one independent variable is involved in any logistic regression. Almost always, two or more such variables will be involved. As in multiple regression, these variables can be either quantitative or qualitative in nature. If of the former variety, scores in the independent variable are construed to represent points along a numerical continuum. With qualitative independent variables, however, scores carry no numerical meaning and only serve the purpose of indicating group membership. In any given logistic regression, the independent variables can be all quantitative, all qualitative, or some of each. Moreover, independent variables can be used individually and/or jointly as an interaction.

When using logistic regression, applied researchers normally collect data on several independent variables, not just one. In the study alluded to earlier in which the dependent variable dealt with nighttime coughing among preschool children, the independent variables dealt with the child's sex and birth weight, the possible presence of pets and dampness problems in the home, whether or not the parents smoked or had asthma, and whether or not the child attended a day care center. It is not unusual to see this many independent variables utilized within logistic regression studies.

As indicated earlier, a subset of the independent variables in a typical logistic regression are control variables. Such variables are included in a logistic regression so the researcher can assess the "pure" relationship between the remaining independent variable(s) and the dependent variable. In a very real sense, control variables are included because of suspected confounding that would muddy the water if the connection between the independent and dependent variables were examined directly.

In any given logistic regression wherein control is being exercised by means of the inclusion of covariate variables, it may be that only one such variable is involved, or that two or three are used, or that all but one of the independent variables are covariates. It all depends, of course, on the study's purpose and the researcher's ability to identify and measure potentially confounding variables. In the study concerned with preschoolers and chronic coughing at night, all but one of the independent variables were included for control purposes; by so doing, the researchers considered themselves better able to examine the direct influence of day care versus home care on respiratory symptoms.

In Excerpt 16.23, we see a case in which the three kinds of variables of a typical logistic regression are clearly identified. It is worth the time to read this excerpt closely with an eye toward noting the nature and number of these three kinds of variables.

As in all such logistic regressions, the study associated with Excerpt 16.23 had one dependent variable that was dichotomous in nature. That variable was whether children developed cavities in their teeth. In addition, this particular study involved five independent variables (dealing with socioeconomic characteristics of the children's

EXCERPT 16.23 • *Dependent, Independent, and Control Variables*

To determine the independent impact of the socioeconomic variables on ECC [early childhood cavities], a multiple logistic regression model was built using all 5 socioeconomic variables and adjusting for age, family size, and oral health-related behavioral variables as possible confounders.

Source: Willems, S., Vanobbergen, J., Martens, L., and De Maeseneer, J. (2005). The independent impact of household- and neighborhood-based social determinants on early childhood cavities. *Family & Community Health, 28*(2), p. 173.

homes and neighborhood) along with several control variables. Although the term "control variable" does not appear in Excerpt 16.23, the terms "adjusting for" and "possible confounders" indicate that age, family size, and oral health-related behavioral variables were used as control variables.

Many logistic regression studies are like the one associated with Excerpt 16.23 in that they involve one dichotomous dependent variable, multiple independent variables, and multiple control variables. In some logistic regression studies, there will be multiple independent variables and a single control variable. Or, there might be a single independent variable combined with several control variables. It all depends on the goals of the investigation and the researcher's ability to collect data on independent and control variables that are logically related to the dependent variable.

Objectives of a Logistic Regression

Earlier in this chapter, we pointed out that researchers use bivariate and multiple regression in order to achieve one of two main objectives: explanation or prediction. So it is with logistic regression. In many studies, the focus is on the noncontrol independent variables, with the goal being to identify the extent to which each one plays a role in explaining why people have the status they do on the dichotomous dependent variable. In other studies, the focus is primarily on the dependent variable and how to predict whether or not people will end up in one or the other of the two categories of that outcome variable.

Excerpt 16.24 illustrates the kind of logistic regression in which explanation is the goal. In this study, the researcher was interested in examining potential explanations as to why first-generation college students either do or don't complete their undergraduate programs. The focus in this study was not so much on the dichotomous dependent variable (completed or did not complete college) as it was on the independent variables that might explain why some first-generation students are successful in college while others aren't.

EXCERPT 16.24 • *Logistic Regression and Explanation*

The greatest benefits for explaining college success of first-generation students result from thorough examination of both precollege attributes of students and the quality of their interactions with institutions of higher education. However, this study will only investigate the effects of precollege attributes of students on their attrition and degree completion behavior, mainly due to a lack of available time-varying items in the study data, such as academic and social integration. . . . Since logistic regression was identified as an appropriate statistical method for the analysis, graduation status was coded as 1 in the dichotomous dependent variables.

Source: Ishitani, T. T. (2006). Studying attrition and degree completion behavior among first-generation college students in the United States. *Journal of Higher Education, 77*(5), pp. 865, 887.

In Excerpt 16.25, we see a case in which logistic regression was used for predictive purposes. In the article associated with this excerpt, the researcher developed an equation for predicting whether movies would or wouldn't win the Academy Award for Best Picture. Near the end of the research report, the author cautioned that his prediction formula should not be used to make gambling bets. As he explained, betting on the Academy Awards (even in Las Vegas) is illegal!

EXCERPT 16.25 • *Logistic Regression and Prediction*

The Academy Awards present a unique opportunity to explore voter preferences. Every year the Academy of Motion Picture Arts and Sciences vote for the Best Picture of the Year. There are many influences to their decision. This study seeks to survey and weigh these influences. This paper analyzes the previous forty years of Best Picture nominations for characterizations including personnel, genre, marketing and records in other award competitions. Using a logistic regression model, each variable's effect on the odds of a given film winning the Best Picture Award is estimated.

Source: Kaplan, D. (2006). And the Oscar goes to . . .: A logistic regression model for predicting Academy Award results. *Journal of Applied Economics & Policy, 25*(1), p. 23.

Odds, Odds Ratios, and Adjusted Odds Ratios

Because the concept of **odds** is so important to logistic regression, let's consider a simple example that illustrates what this word does (and doesn't) mean. Suppose you have a pair of dice that are known to be fair and not loaded. If you were to roll these two little cubes and then look to see if you rolled a pair (two of the same number), the answer would be yes or no. Altogether, there are 36 combinations of how the dice might end up, with six of these being pairs. On any roll, therefore, the probability of getting a pair is 6/36, or .167. (Naturally, the probability of not getting a pair would be .833.) Clearly, it's more likely that you'll fail than succeed in your effort to roll a pair. But we can be even more precise than that. We could say that the odds are 5-to-1 against you, meaning that you are five times more likely to roll a nonpair than a pair.

Most researchers utilize logistic regression so they can discuss the explanatory or predictive power of each independent variable using the concept of odds. They want to be able to say, for example, that people are twice as likely to end up one way on the dependent variable if they have a particular standing on the independent variable being considered. For example, in one recent study on the impact of child maltreatment on later delinquency, the researchers summarized their finding by saying that "youth maltreated during adolescence are about five times as likely to be arrested as are those never maltreated." In another study, the researchers found that "Snowboarders who wore protective wrist guards were half as likely to sustain wrist injuries as those who did not wear guards."

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Odds ratio

After performing a logistic regression, researchers will often cite the **odds ratio** for each independent variable, or at least for the independent variable(s) not being used for control purposes. The odds ratio is sometimes reported as **OR,** and it is analogous to r^2 in that it measures the strength of association between the independent variable and the study's dependent variable. However, the odds ratio is considered by many people to be a more user-friendly concept than the coefficient of determination. Because the odds ratio is so central to logistic regression, let's pause for a moment to consider what this index means.

Imagine that two very popular TV programs end up going head-to-head against each other in the same time slot on a particular evening. For the sake of our discussion, let's call these programs A and B. Also imagine that we conduct a survey of folks in the middle of this time slot in which we ask each person two questions: (1) What TV show are you now watching? and (2) Are you a male or a female? After eliminating people who either were not watching TV or were watching something other than program A or B, let's suppose we end up with data like that shown in Figure 16.2.

		TV Program Being Watched	
		Program A	Program B
Gender	Male	200	100
	Female	50	150

FIGURE 16.2 ***Hypothetical Data Showing Gender Preferences for Two TV Programs***

As you can see, both TV programs were equally popular among the 500 people involved in our study. Each was being watched by 250 of the folks we called. Let's now look at how each gender group spread itself out between the two programs. To do this, we'll arbitrarily select Program A and then calculate, first for males and then for females, the odds of watching Program A. For males, the odds of watching Program A are 200 ÷ 100 (or 2 to 1); for females, the odds of watching this same program are 50 ÷ 150 (or 1 to 3). If we now take these odds and divide the one for males by the one for females, we obtain the ratio of the odds for gender relative to Program A. This OR would be equal to (2 ÷ 1) ÷ (1 ÷ 3), or 6. This result tells us that among our sampled individuals, males are six times more likely to be watching Program A than women. Stated differently, gender (our independent variable) appears to be highly related to which program is watched (our dependent variable).

In our example involving gender and the two TV programs, the odds ratio was easy to compute because there were only two variables involved. As we have seen, however, logistic regression is typically used in situations where there are more than two independent variables. When multiple independent variables are involved, the procedures for computing the odds ratio become quite complex; however, the basic idea of the odds ratio stays the same.

Consider Excerpts 16.26 and 16.27. Notice that the phrases "an 85% reduction" and "a 66% reduction" appear in the first of these excerpts, whereas the phrase "1.3 times more likely" appears in the second excerpt. Most people can understand

EXCERPTS 16.26–16.27 • *Odds Ratio and Adjusted Odds Ratio*

In comparing breastfeeding behaviors for immigrant versus nonimmigrant participants, we found that immigrants were significantly more likely to breastfeed than were nonimmigrants. Mothers born in the United States had an 85% reduction in the odds of breastfeeding (OR = 0.150, P < .01), and a 66% reduction in the odds of breastfeeding at 6 months (OR = 0.344, P < .01).

Source: Gibson-Davis, C. M., and Brooks-Gunn, J. (2006). Couples' immigration status and ethnicity as determinants of breastfeeding. *American Journal of Public Health, 96*(4), p. 643.

When adjusted for physician demographics and practice characteristics, specialty was still a strong predictor of program familiarity. Again, pulmonologists (adjusted odds ratio [OR] = 1.205), general/family practice physicians (OR = 1.000), and cardiologists (OR = 0.856) had the biggest rates of familiarity. . . . Increasing age was associated with lower odds of referral, and female physicians were 1.3 times more likely than male physicians to have referred patients to smoking cessation programs.

Source: Steinberg, M. B., Alvarez, M. S., Delnevo, C. D., Kaufman, I., and Cantor, J. C. (2006). Disparity of physicians' utilization of tobacco treatment services. *American Journal of Health Behavior, 30*(4), p. 381.

conclusions such as these even though they are unfamiliar with the statistical formulas needed to generate an odds ratio type of conclusion. In addition, I suspect you can see, without difficulty, that whether an odds ratio ends up being greater than 1 or less than 1 is quite arbitrary. It all depends on the way the sentence is structured. For example, the researchers who gave us Excerpt 16.27 would have presented an OR of .77 in the final sentence (and they would have said "about three-fourths as likely") if the position of the words "female" and "male" had been reversed.

When the odds ratio is computed for a variable *without* considering the other independent variables involved in the study, it can be conceptualized as having come from a bivariate analysis. Such an OR is said to be a crude or unadjusted odds ratio. If, as is usually the case, the OR for a particular variable is computed in such a way that it takes into consideration the other independent variable(s), then it is referred to as an **adjusted odds ratio.** By considering all independent variables jointly so as to assess their connections to the dependent variable, researchers often say that they are performing a multivariate analysis.

Adjusted odds ratio

To see an example of an adjusted odds ratio, consider once again Excerpt 16.27. Notice that this excerpt begins with the words "when adjusted for physician demographics and practice characteristics." Because these variables were taken into account, all of the OR numbers in this excerpt (including 1.3) are adjusted odds ratios. The first number, 1.205, is clearly shown that way. The researchers expect us to apply the word "adjusted" to the other OR numbers they present.

Tests of Significance

When using logistic regression, researchers usually conduct tests of significance. As in multiple regression, such tests can be focused on the odds ratios (which are like regression coefficients) associated with individual independent variables or on the full regression equation. Whereas tests on the full regression equation typically represent the most important test in multiple regression, tests on the odds ratios in logistic regression are considered to be the most critical tests the researcher can perform.

When the odds ratio or adjusted odds ratio associated with an independent variable is tested, the null hypothesis says that the population counterpart to the sample-based OR is equal to 1. If the null hypotheses were true (with OR = 1), it would mean that membership in the two different categories of the dependent variable is unrelated to the independent variable under consideration. For this null hypothesis to be rejected, the sample value of OR must deviate from 1 further than would be expected by chance.

Researchers typically use one of two approaches when they want to test an odds ratio or an adjusted odds ratio. One approach involves setting up a null hypothesis, selecting a level of significance, and then evaluating the H_0 either by comparing a test statistic against a critical value or by comparing the data-based p against α. In Excerpts 16.28 and 16.29, we see two examples in which this first approach was used.

Notice in Excerpt 16.28 that the researchers used the **Wald test** to see if the odds ratio was statistically significant. This test is highly analogous to the t-test in

EXCERPTS 16.28–16.29 • *Testing an OR or an AOR for Significance*

Scores on the SST at recruitment were significant predictors of depression severity [mildly or severely depressed] at follow-up (Wald's $\chi^2(1) = 6.73$, $p < .01$), with an odds ratio of 0.69.

Source: Thomas, S. A., and Lincoln, N. B. (2006). Factors relating to depression after stroke. *British Journal of Clinical Psychology, 45*(1), p. 55.

Table 2 [not shown here] presents logistic regression results for bullies. As predicted, the friends of bullies reported more aggression, both in the entire sample (*AOR* [adjusted odds ratio] = 1.32, $p < .0001$) and in the subsample of females ($AOR = 1.46$, $p < .006$).

Source: Mouttapa, M., Valente, T., Gallaher, P., Rohrbach, L. A., and Unger, J. B. (2004). Social Network predictors of bullying and victimization. *Adolescence, 39*(154), p. 324.

multiple regression that is used to see if a beta weight is statistically significant. These two tests are only analogous, however, for they differ not only in terms of the null hypothesis but also in the kinds of calculated and critical values used to test the H_0. As illustrated in Excerpt 16.28, the Wald test is tied to a theoretical distribution symbolized by χ^2 rather than *t*. (This is the chi-square distribution.) In Excerpt 16.29, the test used to test the adjusted odds ratios is not specified. The researchers probably used the Wald test, but they may have used an alternative test procedure.

The second way a researcher can test an odds ratio is through the use of a confidence interval. The CI rule of thumb for deciding whether to reject or retain the null hypothesis is the same as when CIs are used to test means, *r*s, the difference between means, or anything else. If the confidence interval overlaps the pinpoint number in the null hypothesis, the null hypothesis will be retained; otherwise, H_0 is rejected. Excerpt 16.30 illustrates how a CI can be used to test an odds ratio. Take

EXCERPT 16.30 • *Testing an Odds Ratio via a Confidence Interval*

The use of spasm reduction interventions, however, was found to [significantly] decrease the likelihood of a successful outcome (OR = 0.77, 95% CI = 0.60–0.98). That is, the odds of achieving an increase of 14 points or greater in PCS-12 scores were reduced 23% in patients receiving spasm reduction interventions.

Source: Jewell, D. V., and Riddle, D. L. (2005). Interventions that increase or decrease the likelihood of a meaningful improvement in physical health in patients with sciatica. *Physical Therapy, 85*(11), p. 1146.

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Multicollinear

the time to look closely at this excerpt's CI, note its ends, and then recall that the pinpoint number in the null hypothesis being tested is 1.0. Can you see why the researchers' OR of .77 was considered to represent a significant reduction in the likelihood of success if patients were treated by spasm reduction intervention?

As indicated previously, it is possible in logistic regression to test whether the collection of independent and control variables do a greater-than-chance job of accounting for the status of people on the dependent variable. This test is typically made with a special form of the chi-square test. This test has the same symbol (χ^2) as the test used to evaluate individual ORs or AORs; with this version, however, researchers usually talk about it in terms of it being a test of the **model.** In Excerpt 16.31, we see an example of this kind of test.

EXCERPT 16.31 • *Testing the Full Logistic Regression Model*

In order to examine, more comprehensively, the effects of potential predictors, logistic regression was performed on the data. Age at onset, clinical severity of psoriasis, alexithymia, beliefs about time-line, consequences, and emotional causes were the predictor variables that were entered into the regression with adversarial growth dummy coded. . . . The regression model was significant ($-2 \log L = 55.63$, $\chi^2 = 25.83, p = .0001$).

Source: Knussen, C., Tolson, D., Swan, I. R. C., Stott, D. J., Brogan, C. A., and Sullivan, F. (2005). Adversarial growth in patients undergoing treatment for psoriasis: A prospective study of the ability of patients to construe benefits from negative events. *Psychology, Health & Medicine, 10*(1), p. 50.

Final Comments

As we conclude this chapter, we need to consider five additional regression-related issues. These concerns deal with multicollinearity, control, practical significance, the inflated Type I error risk, and cause. If you will keep these issues in mind as you encounter research reports based on bivariate, multiple, and logistic regression, you will be in a far better position to both decipher and critique such reports.

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Multicollinearity

In multiple and logistic regression, the independent and control variables should not be highly correlated with one another. If they are, a condition called **multicollinearity** is said to exist. Excerpts 16.32 and 16.33 illustrate the way dedicated researchers will demonstrate that they know about this potential problem and will examine their data to see whether their regressions would be "messed up" by an undesirable network of intercorrelations among their independent variables. In both of these excerpts, the technique of multiple regression was used. It should be noted, however, that multicollinearity can be a problem in logistic regression

EXCERPTS 16.32–16.33 • *Multicollinearity*

Multicolinearity among the explanatory variables was assessed by calculating the tolerance level and bivariate correlations. A tolerance level of .40 or less was considered an indication of high multicolinearity. The tolerance level of each explanatory variable was greater than .50, and the bivariate correlation coefficients were less than .45, indicating that each explanatory variable contributed unique information.

Source: Greene, B. L., Haldeman, G. F., Kaminski, A., Neal, K., Sam Lim, S., and Conn, D. L. (2006). Factors affecting physical activity behavior in urban adults with arthritis who are predominantly African-American and female. *Physical Therapy, 86*(4), p. 514.

An interaction term was created as a product of SM and social leisure in order to test the hypothesis that the relationship of social leisure to life quality is moderated by level of SM. Aiken and West (1991) warned that statistical interactions, created as a product of two independent variables, can create problems of multicollinearity as the interaction term tends to be highly correlated to the variables used to create it. One method they offered to control for such problems is create "centered" variables in which the original variable is transformed into a deviation score from the variable mean. These deviation scores are then used in creation of the interaction term. The procedure outlined above was used in this study to minimize multicollinearity.

Source: Lee, Y., and McCormick, B. P. (2006). Examining the role of self-monitoring and social leisure in the life quality of individuals with spinal cord injury. *Journal of Leisure Research, 38*(1), pp. 10–11.

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studies as well. Look for researchers to address this concern regardless of the type of regression they use.

In the discussions of both hierarchical multiple regression and logistic regression, we saw that researchers often incorporate control or covariate variables into their analyses. Try to remember that such **control** is very likely to be less than optimal. This is the case for three reasons. First, one or more important confounding variables might be overlooked. Second, potential confounding variables that *are* measured are likely to be measured with instruments possessing less than perfect reliability. Finally, recall that the analysis of covariance undercorrects when used with nonrandom groups that come from populations that differ on the covariate variable(s). Regression suffers from this same undesirable characteristic.

My next concern relates to *the distinction between statistical significance and practical significance.* We have considered this issue in connection with tests focused on means and *r*s, and it is just as relevant to the various inferential tests used by researchers within regression analyses. In Excerpt 16.34, we see a case in which a pair of researchers attended to the important distinction between useful and trivial findings. These researchers deserve high praise for realizing (and warning their

EXCERPT 16.34 • *Practical versus Statistical Significance*

For the school counselors, only one significant variable entered the equation: the GRCS Restrictive Emotionality subscale score ($p < .0001$), with higher Restrictive Emotionality scores predicting fewer prestige choice preferences. Although this regression equation was statistically significant, $F(1, 98) = 15.98, p < .0001$, it accounted for only 14% of the variance in prestige choice score. A significant equation was also found for the engineers, $F(1, 98) = 5.15, p = .0075$, with two MRNS subscale scores being significant predictors. Both the Status ($p = .0102$) and Toughness ($p = .0174$) subscales predicted the prestige choice score. Again, although the model was statistically significant, these two variables combined accounted for less than 10% of the prestige score variance. Given the very low R^2 values, neither of these two prediction equations has much practical importance.

Source: Dodson, T. A., and Borders, L. D. (2006). Men in traditional and nontraditional careers: Gender role attitudes, gender role conflict, and job satisfaction. *Career Development Quarterly, 54*(4), p. 290.

readers) that inferential tests can yield results that are statistically significant without being important in a practical manner.

In many research reports, researchers make a big deal about a finding that seems small and of little importance. Perhaps such researchers are unaware of the important distinction between practical and statistical significance, or it may be that they know about this distinction but prefer not to mention it due to a realization that their statistically significant results do not matter very much. Either way, it is important that *you* keep this distinction in mind whenever you are on the receiving end of a research report.

Not too long ago, I came across an article (in a technical research journal) concerning youth and adolescents, their use of sunscreen and tanning beds, and their rate of sunburns. It turned out that there was a statistically significant connection between age (one of the predictor variables) and sunburning (one of the outcome variables). This finding was based on an adjusted odds ratio produced by a logistic regression. How large do you think this AOR was? Tucked away in one of the article's tables, I found it. The table contained this information: "adjusted OR = 1.09 (1.01–1.18)." In my opinion, this finding has questionable worth because the number 1.09 is so close to the null hypothesis value of 1.00. You have the right to make similar kinds of judgments when you read or listen to research reports.

As we have seen in the excerpts of previous chapters, competent researchers are sensitive to the inflated Type I error risk that occurs if a given level of significance, say .05, is used multiple times within the same study when different null hypotheses are tested. Give credit to researchers when they apply the Bonferroni adjustment procedure (or some other comparable strategy) within their regression studies. Excerpt 16.35 provides an example of this.

EXCERPT 16.35 • *Bonferroni Adjustment Procedure*

To investigate our research questions, the data were analyzed using a series of hierarchical regression analyses. The independent variables included gender in the first step of each equation and universal-diverse orientation (MGUDS-S) and emotional intelligence (EIS) in the second step. The dependent variables were the four empathy subscales of the IRI: perspective taking, empathic concern, fantasy, and personal distress. A Bonferroni adjusted alpha level of .05/4 or .01 was used to test the significance of each regression analysis.

Source: Miville, M. L., Carlozzi, A. F., Gushue, G. V., Schara, S. L., and Ueda, M. (2006). Mental health counselor qualities for a diverse clientele: Linking empathy, universal-diverse orientation, and emotional intelligence. *Journal of Mental Health Counseling, 28*(2), p. 159.

As we turn to my last concern, recall the important point made in Chapter 3 that a bivariate correlation—even if found to be statistically significant with a large r^2 value—should not be automatically interpreted to mean that a **causal link** exists between the two variables on which data have been collected. The same point holds for bivariate, multiple, and logistic regression. Even when the results suggest strongly that the regression has achieved its predictive or explanatory objective, the analysis is correlational in nature. Even when multiple control variables are included in the model, a regression analysis is simply correlational in nature.

In Excerpt 16.36, we see a case in which a team of researchers provides their readers with a clear warning about cause-and-effect. In essence, that warning says *not* to think that the study's primary independent variable (mental health) had a causal influence on the study's dependent variable (physical health). I salute these researchers for providing this warning and for explaining, in the excerpt's final sentence, why it would be wrong to impute cause-and-effect into the study's findings.

EXCERPT 16.36 • *Regression and Cause-and-Effect*

The goal of the current study was to compare the relationship between mental health problems and health status in a large sample of low-income children with and without serious emotional disorders (SED). . . . SED status contributed significantly to predictions of all three health-status indicators. . . . Neither this study [using hierarchical multiple regression] nor the research reviewed for it provides an explanation of the relationship between physical and mental health problems, of course; one might cause the other, or a third variable may influence both types of health problems.

Source: Combs-Orme, T., Helfinger, C. A., and Simpkins, C. G. (2002). Comorbidity of mental health problems and chronic health conditions in children. *Journal of Emotional and Behavioral Disorders, 10*(2), pp. 117, 121.