



Toward a New Classification of Nonexperimental Quantitative Research

by Burke Johnson

A substantial proportion of quantitative educational research is nonexperimental because many important variables of interest are not manipulable. Because nonexperimental research is an important methodology employed by many researchers, it is important to use a classification system of nonexperimental methods that is highly descriptive of what we do and also allows us to communicate effectively in an interdisciplinary research environment. In this paper, the present treatment of nonexperimental methods is reviewed and critiqued, and a new, two-dimensional classification of nonexperimental quantitative research is proposed. The first dimension is based on the primary “research objective” (i.e., description, prediction, and explanation), and the second dimension is called the “time” dimension (i.e., cross-sectional, longitudinal, and retrospective).

The focus of this paper is on nonexperimental quantitative research as it is currently presented in educational research methods textbooks. Nonexperimental quantitative research is an important area of research for educators because there are so many important but nonmanipulable independent variables needing further study in the field of education. Here is the way one eminent educational research methodologist (Kerlinger, 1986) put it:

It can even be said that nonexperimental research is more important than experimental research. This is, of course, not a methodological observation. It means, rather, that most social scientific and educational research problems do not lend themselves to experimentation, although many of them do lend themselves to controlled inquiry of the nonexperimental kind. Consider, Piaget’s studies of children’s thinking, the authoritarianism studies of Adorno et al., the highly important study of *Equality of Educational Opportunity*, and McClelland’s studies of need for achievement. If a tally of sound and important studies in the behavioral sciences and education were made, it is possible that nonexperimental studies would out-number and outrank experimental studies. (pp. 359–360)

Kerlinger’s point about the importance of nonexperimental research is true even when interest is in studying cause and effect relationships. Although the strongest designs for studying cause and effect are the various randomized experiments, the fact remains that educational researchers are often faced with the situation in which neither a randomized experiment nor a quasi-experiment (with a manipulated independent variable) is feasi-

ble (e.g., in the presence of independent variables such as educational spending, school choice, public versus private schools, class size, length of school year, illicit drug use, teen pregnancy, mental retardation, learning disabilities, parenting styles, learning styles, dropping out of school, and school violence). Nonexperimental research may also be important even when experiments are possible as a means to suggest or extend experimental studies, to provide corroboration, and to provide increased evidence of the external validity of previously established experimental research findings. In short, nonexperimental research is frequently an important and appropriate mode of research in education.¹

In the last section of this paper I present an integrative and parsimonious typology that can be used to classify nonexperimental quantitative research. But first, I discuss the causal-comparative versus correlational research dichotomy as it is presented in several educational research texts (e.g., Charles, 1998; Gay & Airasian, 2000; Martella, Nelson, & Marchand-Martella, 1999), list the similarities and differences between causal-comparative and correlational research (according to the authors of several leading textbooks), examine potential sources of the belief that causal-comparative research provides stronger evidence of causality than correlational research, and make suggestions about how we approach the issue of causality in nonexperimental research.

Causal-Comparative Versus Correlational Research in Current Textbooks

Several educational research methodologists make a distinction in their texts between the two nonexperimental methods called *causal-comparative research* and *correlational research* (e.g., Charles, 1998; Gay & Airasian, 2000; Martella et al., 1999). According to these authors, a primary distinction between these two methods is that causal-comparative includes a categorical independent and/or dependent variable (hence the word *comparative* implying a group comparison) and correlational only includes quantitative variables. These authors also suggest, inappropriately, that causal-comparative research provides better evidence of cause and effect relationships than correlational research. The following quotes from the latest edition of Gay’s popular text (Gay & Airasian, 2000) demonstrate these points:

Causal-comparative studies attempt to establish cause-effect relationships; correlational studies do not. . . . Causal-comparative studies involve comparison, whereas correlational studies involve relationship. (p. 350)

Causal-comparative and experimental research always involves the comparison of two or more groups or treatments. (p. 41)

Correlational research involves collecting data in order to determine whether, and to what degree, a relationship exists between two or more *quantifiable* variables. (p. 321; italics added)

The purpose of a correlational study is to determine relationships between variables or to use these relationships to make predictions. . . . Variables that are highly related to achievement may be examined in *causal-comparative or experimental studies*. (pp. 321–322; italics added)

Correlational research never establishes cause-effect links between variables. (p. 13; italics added)

Charles (1998) says, “Causal-comparative research *strongly suggests* cause and effect” (p. 305; italics added) but that correlational research can only be used to “examine the possible existence of causation” (p. 260). He specifically says that “This type of research [causal-comparative] can suggest causality more persuasively than correlational research, but less persuasively than experimental research” (p. 34). In one of the newer educational research methods books on the market, Martella et al. (1999) state the following:

Causal-comparative research is considered to have a lower constraint level than experimental research because no attempt is made to isolate the effects of a manipulable independent variable on the dependent variable. . . . Unlike causal-comparative research, [in correlational research] there is usually just one group, or at least groups are not compared. For this reason, *correlational research has a lower constraint level than causal-comparative research*. There is not an active attempt to determine the effects of the independent variable in any direct way. (p. 20; italics added)

I do not want to leave the impression that all presentations of causal-comparative and correlational research are misleading. For example, some authors of educational research texts (Fraenkel & Wallen, 2000; Gall, Borg, & Gall, 1996) make a distinction that causal-comparative research has a categorical variable and requires a specific set of statistical analysis models (e.g., ANOVA) and that correlational research includes quantitative variables and requires its specific set of statistical analysis models (e.g., regression). However, these authors do *not* make the claim that causal-comparative research provides superior evidence for establishing cause and effect than does correlational research. Gall et al. (1996) explicitly and correctly make this important point:

The causal-comparative method is the simplest quantitative approach to exploring cause-and-effect relationships between phenomena. It involves a particular method of analyzing data to detect relationships between variables. The correlational method, discussed in chapter 11, is another approach to achieve the same goal. (p. 380)

The correlational approach to analyzing relationships is subject to the same limitations with respect to causal inference as the causal-comparative approach. (p. 413)

Note also that some authors (Johnson & Christensen, 2000; Slavin, 1992) choose to include but to minimize the distinction between causal-comparative and correlational research, and many authors (e.g., Creswell, 1994; Kerlinger & Lee, 2000; Krathwohl, 1997; Pedhazur & Schmelkin, 1991; Tuckman, 1994) choose not to make the causal-comparative and correlational compari-

son at all. Obviously, there is major disagreement among leading authors of educational research texts about the status of causal-comparative and correlational research.

Based on the above quotations, and the space allocated to these two methods in several popular textbooks (e.g., Fraenkel & Wallen, 2000; Gall et al., 1996; Gay & Airasian, 2000), it should not be surprising that almost 80% ($n = 330$) of the participants in an Allyn and Bacon Research Methods Survey of teachers of educational research said that the distinction between causal-comparative research and correlation research should be retained (Allyn & Bacon, 1996). These terms have become part of the nonmaterial culture in education. Although only a small minority of the research methods teachers replying to a follow-up open-ended question (asking why they felt the distinction was needed) showed some confusion about causality in nonexperimental research, it is a problem when any *teachers* of educational research are confused about causality. It is also a problem when the writers of the “most widely used educational research text ever published” (i.e., Gay & Airasian, 2000)² as well as other texts (e.g., Charles, 1998; Martella et al., 1999) clearly suggest that causal-comparative research provides superior evidence of causality than correlational research.

If, as I discuss later, the primary distinction between a causal-comparative and a correlational study is the scaling of the independent and/or dependent variable (and not the manipulation of the independent variable), then an obvious question is “Why can one supposedly make a superior causal attribution from a causal-comparative study?” The answer is that this contention is completely without basis. The point Martella et al. (1999) make about causal-comparative research comparing groups but correlational research only looking at one group also has nothing to do with establishing evidence of causality (e.g., a structural equation model based on multiple quantitative variables would also be based on “one group”). Likewise, the fact that some writers choose to *label* the independent variable a “predictor” variable in correlational research but not in causal-comparative has nothing to do with establishing evidence of causality.

To illustrate the point about variable scaling, consider the following example. Suppose one is interested in learning whether two variables, “time spent studying per day” during the week before a test (based on a self-reported, retrospective question) and actual “test scores” (recorded by the teachers), are associated. If time spent studying is measured in minutes per day, then a “correlational” study results. If, however, time is artificially dichotomized into two groups—10 minutes or less per day and more than 10 minutes per day—a “causal-comparative” study results. Note that there are no controls included in either of these two hypothetical studies. The only true distinction between these two studies is the scaling of the variables. This is a trivial distinction and does not warrant the claim that the causal-comparative study will produce more meaningful evidence of causality. Third variables (i.e., confounding extraneous variables) such as ability, age, and parental guidance could be affecting study time and exam scores in both of the above studies. For another example, there is no reason to believe a stronger causal claim can be made from a study without controls measuring the relationship between gender and test grades (a causal-comparative study) than from a study without controls measur-

ing the relationship between time spent studying for a test and test grades (a correlational study). (Note that the researcher could calculate a simple correlation coefficient in both of these cases.) The point is that only a relationship between two variables would have been demonstrated.

The first contention in this paper is that, *ceteris paribus*, causal-comparative research is neither better nor worse in establishing evidence of causality than correlational research.³ When one compares apples to apples (e.g., the simple cases of causal-comparative and correlational research) and oranges to oranges (e.g., the more advanced cases), it becomes clear that causal-comparative research is not any better than correlational research for making causal attributions. I am defining the *simple cases* of causal-comparative and correlational research here as studies that include *two variables and no controls*, and *advanced cases* as studies where *controls are included*. It is essential that we understand that what is always important when attempting to make causal attributions is the elimination of *plausible rival explanations* (Cook & Campbell, 1979; Huck & Sandler, 1979; Johnson & Christensen, 2000; Yin, 2000). It is also important to understand that *one can attempt to eliminate selected rival explanations in both causal-comparative and correlational research*. The second contention in this paper is that the terms *causal-comparative* and *correlational* research are outdated and should be replaced by more current terminology. The third contention is that all non-experimental quantitative research in education can easily and effectively be classified along two key dimensions. These ideas are developed in the remainder of this paper.

What Are the Similarities and Differences Between Causal-Comparative and Correlational Research Methods?

Causal-comparative and correlational methods, as defined in educational research textbooks (e.g., Charles, 1998; Fraenkel & Wallen, 2000; Gall et al., 1996; Gay & Airasian, 2000; Martella et al., 1999), are similar in that both are nonexperimental methods because they lack manipulation of an independent variable which is under the control of the experimenter and random assignment of participants is not possible. This means, among other things, that the variables must be observed as they occur naturalistically.

As a result, the key and omnipresent problem in nonexperimental research is that an observed relationship between an independent variable and a dependent variable may be partially or fully *spurious* (Davis, 1985). A spurious relationship is a non-causal relationship; it is the result of the operation of one or more *third variables*. For an example of the “third variable problem,” note that self-reported “gender role identification” (i.e., self-identification as masculine or feminine) and high school “algebra performance” may be statistically associated. However, much or all of that relationship would probably be due to the joint influence of the third variable “socialization.” Perhaps both gender role identification and algebra performance are affected by socialization processes. Because of the lack of manipulation of the independent variable and the problem of spuriousness, neither causal-comparative nor correlational research can provide evidence for causality as strong as that which can be provided by a study based on a randomized experiment or a strong quasi-

experimental design (such as the regression discontinuity design or the time series design). Indeed, even the more sophisticated theory testing or confirmatory approaches relying on structural equation modeling (which are “correlational”) provide relatively weak evidence of causality (when based on nonexperimental data) as compared to the evidence obtained through randomized experiments.

Causal-comparative and correlational studies differ on the scaling of the independent and/or dependent variables. That is, according to popular textbooks (e.g., Charles, 1998; Fraenkel & Wallen, 2000; Gall et al., 1996; Gay & Airasian, 2000), causal-comparative studies include at least one categorical variable and correlational studies include quantitative variables. The type of independent variable used in most causal-comparative and correlational studies is an *attribute variable* (Kerlinger, 1986). These

Obviously, there is major disagreement among leading authors of educational research texts about the status of causal-comparative and correlational research.

rarely manipulable variables are called attribute variables because they represent characteristics or “attributes” of different people. The attribute variable concept is easily generalized to non-human units of analysis (e.g., schools, books, cultures, etc.). Some categorical independent variables that cannot be manipulated and might be used in a “causal-comparative” study are gender, parenting style, learning style, ethnic group, college major, party identification, type of school, marital status of parents, retention in grade, type of disability, presence or absence of an illness, drug or tobacco use, and any personality trait that is operationalized as a categorical variable (e.g., extrovert versus introvert). Some quantitative independent variables that cannot be manipulated and might be used in a “correlational study” are intelligence, aptitude, age, school size, income, job satisfaction, GPA, amount of exposure to violence in the media, and any personality trait that is operationalized as a quantitative variable (e.g., degree of extroversion). Again, the key characteristic of the independent variables used in causal-comparative and correlational studies is that they either cannot be manipulated or they were not manipulated for various reasons (e.g., because of ethical concerns or a lack of resources).

Causal-comparative and correlational studies are similar in that both are used to examine relationships among variables. The

data from both of these approaches are usually analyzed using the general linear model (GLM), and it is well known that all special cases of the GLM are correlational (e.g., Kerlinger, 1986; Knapp, 1978; McNeil, Newman, & Kelly, 1996; Tatsuoka, 1993; Thompson, 1999). Given this, it is misleading to suggest, as is sometimes done in educational research texts, that only correlational research examines relationships.

Causal-comparative and correlational studies are similar on the techniques available for controlling confounding variables. For example, one can statistically control for confounding variables in both approaches by collecting data on the key confounding extraneous variables and including those variables in the GLM. Likewise, one can eliminate the relationship between selected confounding and independent variables (regardless of their scaling) using matching or quota sampling. The equivalent of the causal-comparative matching strategy of equating groups on specific matching variables in correlational research is to use a quota sampling design to select data such that the independent variable is uncorrelated and therefore unconfounded with specific extraneous (“matching”) variables (Johnson & Christensen, 2000). Today, statistical control is usually preferred over matching (Judd, Smith, & Kidder, 1991; Rossi, Freeman, & Lipsey, 1999) when reliable control variables are available.

According to Gay and Airasian (2000), causal-comparative and correlational research have different research purposes. In particular, these authors suggest that the purpose of causal-comparative research is to examine causality and the purpose of correlational research is to examine relationships and make predictions. This is misleading because, first, one can also examine relationships and make predictions in the presence of nonmanipulated categorical variables (i.e., in causal-comparative research), and, second, some evidence of causality can be obtained by controlling for confounding variables and ruling out plausible rival hypotheses in both causal-comparative *and* correlational research. However, the idea of making a distinction within non-experimental quantitative research between approaches dealing with causality and those that do not deal with causality *does* have merit. This idea is explained below, but, first, I examine the origin of the belief that causal-comparative research provides stronger evidence for causality than correlational research.

Where Did the Idea That Causal-Comparative is Superior Originate?

The term *causal-comparative* appears to have originated in the early 20th century (see Good, Barr, & Scates, 1935). The early writers did *not*, however, contend that evidence for causality based on causal-comparative research was superior to evidence based on correlational research. For example, according to Good et al. (1935),

Typically it [causal-comparative] does not go as far as the correlation method which associates a given amount of change in the contributing factors with a given amount of change in the consequences, however large or small the effect. The method [causal-comparative] always starts with observed effects and seeks to discover the antecedents of these effects. (p. 533; italics added)

The correlation method . . . enables one to approach the problems of causal relationships in terms of degrees of both the contributing and the dependent factors, rather than in terms of the dichotomies

upon which one must rely in the use of the causal-comparative method. (p. 548)

It was also known at the time that selected extraneous variables can be partialled out of relationships in correlational research.⁴ This idea is illustrated in the following quote (from Good et al., 1935):

For the purpose of isolating the effects of some of these secondary factors, a technique generally known as partial correlation is available. It has various names for special forms, including part correlation, semi-partial correlation, net correlation, and joint correlation. . . . That is, the influence of many factors upon each other can be separated so that the relationship of any one of them with the general resulting variable (commonly called in statistics the *dependent* variable) can be determined when this relationship is freed from the influence of any or all of the remaining factors studied. (p. 564)

The fallacious idea that causal-comparative data are better than correlational data for drawing causal inferences appears to have emerged during the past several decades.

There may be several sources that have led to confusion. First, some may believe that causal-comparative research is superior to correlational research for studying causality because a causal-comparative study looks more like an experiment. For example, if a researcher categorized the independent variable it may look more like an experiment than when the independent variable is continuous, because of the popularity of categorical independent variables in experimental research.⁵ A related reason is what I will call the “stereotype” position. According to this position, experimental researchers and causal-comparative researchers know how to control for extraneous variables but correlational researchers do not. In other words, the underlying reason that causal-comparative research is said to be superior to correlational research could be due to an unstated and incorrect assumption that causal-comparative researchers use controls but correlational researchers do not.

Second, perhaps the term *causal-comparative* suggests a strong design but the term *correlational* suggests a simple correlation (and hence a weak design). I sometimes ask my beginning research methods students which approach is stronger for studying cause and effect: causal-comparative or correlational research. Many respond that causal-comparative is stronger. When I ask them why they believe causal-comparative is stronger, they frequently point out that the word *causal* appears in the term *causal-comparative research* but not in the term *correlational research*.

Third, the term *correlational research* has sometimes been used as a synonym for nonexperimental research both in education and in the other social and behavioral sciences. Unfortunately, this use may lead some people to forget that causal-comparative also is a nonexperimental research method (i.e., the independent variable is not manipulated). Causal-comparative research is not experimental research; it is not even quasi-experimental research. Causal-comparative research, just like correlational research, is a nonexperimental research method.

Fourth, perhaps the confusion is linked to a faulty view about the difference between ANOVA (which is linked to causal-comparative research) and correlation/regression (which is linked to correlational research). For example, some writers appear to

believe that ANOVA is used only for explanatory research and correlation/regression is limited to predictive research. It is essential to understand that *correlation and regression (especially multiple regression) can be used for explanatory research (and for the control of extraneous variables) as well as for descriptive and predictive research, and, likewise, ANOVA can be used for descriptive and predictive research as well as for explanatory research* (Cohen & Cohen, 1983; Pedhazur, 1997). ANOVA and MRC (multiple regression and correlation) are both “special cases” of the general linear model, and they are nothing but approaches to statistical *analysis*. The general linear model “does not know” whether the data are being used for descriptive, predictive, or explanatory purposes because the general linear model is only a statistical algorithm.

Fifth, perhaps some students and researchers believe causal-comparative research is superior because they were taught the mantra that “correlation does not imply causation.” It is certainly true that correlation does not, by itself, imply causation. *It is equally true, however, that observing a difference between two or more means does not, by itself, imply causation.* It is unfortunate that this second point is not made with equal force in educational research textbooks. Another way of putting this is that evidence for causality in the simple cases of causal-comparative and correlational research (two variables with no controls) is virtually nonexistent. One simply cannot draw causal conclusions from these simple cases. Some evidence of causality can be obtained by *improving* upon these simple cases by identifying potential confounding variables and attempting to control for them.

Future Directions

We should begin by dropping the terms *causal-comparative research* and *correlational research* from our research methods textbooks because too often they mislead rather than inform. The term *causal-comparative* suggests that it is a strong method for studying causality (Why else would it include the word “cause?”), and the term *correlational* places the focus on a statistical technique rather than on a research technique. Furthermore, correlational/regression techniques are used in correlational, causal-comparative, and experimental research. Writers should have followed Thomas Cook and Donald Campbell’s advice on this issue. Over 20 years ago, in their book on quasi-experimentation and field research, Cook and Campbell (1979) made the following point: “The term *correlational-design* occurs in older methodological literature. . . . We find the term *correlational* misleading since the mode of statistical analysis is not the crucial issue” (p. 6).

It is telling that Fred Kerlinger (1986), who was one of education’s leading research methodologists, made no distinction between causal-comparative and correlational research (or between “ex post facto” research and correlational research). Kerlinger used the term *nonexperimental research*, which is the term that I believe educational research methodologists should readily adopt.⁶ Here is how Kerlinger defined the inclusive term *nonexperimental research*:

Nonexperimental research is systematic empirical inquiry in which the scientist does not have direct control of independent variables because their manifestations have already occurred or because they are inherently not manipulable. Inferences about relations among variables are

made, without direct intervention, from concomitant variation of independent and dependent variables. (1986, p. 348; italics in original)

Although Kerlinger originally (1973) called this type of research *ex post facto* research (which some believe is a synonym for the term *causal-comparative* research), Kerlinger later (1986) dropped the term *ex post facto* (probably because it apparently excludes prospective studies).⁷ An examination of Kerlinger’s examples also clearly shows that his nonexperimental research classification is not limited to studies including at least one categorical variable. Kerlinger was an expert on the general linear model and he would never have contended that causal-comparative studies were inherently superior to correlational studies for establishing evidence of cause and effect.

Next, professors of educational research need to spend more time discussing the issues surrounding causality. I have several specific recommendations for discussions of causality. First, students and beginning researchers need to learn how to think about causality and understand that the scaling of a variable (categorical or quantitative) has nothing to do with evidence of causality. For example, when an independent variable is categorical the comparisons are made between the groups. When an independent variable is quantitative the comparisons can be made for the different *levels* of the independent variable; the presumed effect can also be described through a functional form such as a linear or quadratic model. It is generally a poor idea to categorize a quantitative variable because of the loss of information about amount and process (Kerlinger, 1986; Pedhazur & Schmelkin, 1991).⁸

Second, when interest is in causality, researchers should address the *three necessary conditions for cause and effect* (Blalock, 1964; Cook & Campbell, 1979; Johnson & Christensen, 2000). The first condition is that the two variables must be related (i.e., the relationship or association condition). The second condition is that proper time order must be established (i.e., the temporal antecedence condition). If changes in Variable A cause changes in Variable B, then A must occur before B. The third condition is that an observed relationship must not be due to a confounding extraneous variable (i.e., the lack of alternative explanation condition or the nonspuriousness condition). There must not remain any *plausible* alternative explanation for the observed relationship if one is to draw a causal conclusion. A theoretical explanation or rationale for the observed relationship is also important to make sense of the causal relationship and to lead to hypotheses to be tested with new research data. Randomized experiments are especially strong on all three of the necessary conditions. Generally speaking, however, nonexperimental research is good for identifying relationships (Condition 1), but it is weak on Necessary Conditions 2 (time order) and 3 (ruling out alternative explanations). Nonexperimental research is especially weak on Condition 3 because of the problem of spuriousness.

A potential problem to watch for when documenting relationships is that commonly used statistical techniques may miss the relationship. For example, a Pearson correlation coefficient (or any other measure of linear relationship) will underestimate or entirely miss a curvilinear relationship. Model misspecification can also result in failure to identify a relationship. For ex-

ample, if there is a fully disordinal two-way interaction (where the graph for two groups forms an “X”) there will be no main effects, and therefore if one of the independent variables is excluded from the study and the interaction is not examined, it will appear that there is no relationship between the included variables (even experimental manipulation and randomization are to no avail here). Another important form of model misspecification is when one or more common causes are excluded from the

... all nonexperimental, quantitative research in education can easily and effectively be classified along two key dimensions.

model, resulting in the failure to purge the observed relationship of its spurious components (Bollen, 1989; Davis, 1985). Simpson’s Paradox (Moore & McCabe, 1998) can result in a conclusion (based on a measure of bivariate association) that is opposite of the correct conclusion. One must also be careful in interpreting a relationship when suppression is present (see Cohen & Cohen, 1983; Lancaster, 1999).

Researchers interested in studying causality in nonexperimental research should determine whether an observed relationship (that is presumed to be causal) disappears after controlling for key antecedent or concurrent extraneous variables that represent plausible rival explanations. Researchers must be careful, however, when interpreting the reduction in an observed relationship between two variables after controlling for another variable because controlling for either a *confounding* variable (i.e., one that affects both the independent and dependent variables) or an *intervening* variable (i.e., a mediating variable that occurs after the independent variable and before the dependent variable) will reduce the magnitude of the observed relationship (Pedhazur, 1997). It is essential that this process be guided by theory.

There are many strategies that are helpful in establishing evidence for causality in nonexperimental research. There are several useful strategies that are typically based on data from a single research study: (a) collection of longitudinal data, (b) explication of intervening mechanisms to interpret the relationship, (c) evidence of a dose/response relationship, (d) explicit use of one or more control techniques (e.g., matching, statistical control, etc.), (e) testing alternative hypotheses, (f) cross-validation on large samples, (g) evidence of convergence of findings obtained through triangulation (methods, data, and investigator triangulation) (e.g., Denzin, 1989; Tashakkori & Teddlie, 1998), (h) pattern matching (see Trochim, 1989), (i) selection modeling (see Rindskopf, 1992), and (j) comparison of competing theoretical models.

There are also several strategies that are typically based on data from multiple research studies: (a) empirical tests with new data of theoretical predictions generated from a previous study, (b) replication of findings for corroboration and to rule out chance and sample specific factors, (c) specification of the boundary conditions under which a cause has an effect, by studying different people and settings, (d) evidence of construct validity of causes and effects, and (e) extensive open and critical examination of a theoretical argument by the members of the research community with expertise in the research domain.

Little can be gained from a single nonexperimental research study, and students and researchers must always temper their conclusions. Greater evidence can be obtained through explanatory meta-analytic syntheses (assuming that the included studies are of acceptable quality; see Cordray, 1990) or through other attempts to look for consistency across multiple studies, and through the development of falsifiable theories that have survived numerous disconfirmation attempts (e.g., Bollen, 1989; Maruyama, 1998; Popper, 1959). The strongest nonexperimental quantitative studies usually result from well-controlled prospective panel studies and from confirmatory structural equation (theoretical) models (Johnson & Christensen, 2000).

Current Classifications of Nonexperimental Research

Now, for comparison purposes, I present in Table 1 a list of the nonexperimental quantitative research typologies that are currently used in research textbooks in education and related fields. You can see in the table that the authors clearly disagree on how nonexperimental quantitative research should be categorized.

Several themes are apparent in Table 1. First, the most prominent authors choose not to use the terms *causal-comparative research* and *correlational research* (e.g., Cook & Campbell, 1979; Kerlinger & Lee, 2000; Pedhazur & Schmelkin, 1991). Second, some authors choose to use a single name for most of nonexperimental research. For example, Creswell (1994) uses the term *survey research*, and Best and Kahn (1998) use the term *descriptive research*. Third, the term *survey research* is used very inconsistently by authors within education and across other disciplines. For example, sociological writers (e.g., Babbie, 2001; Neuman, 1997) typically use the term *survey research* to refer to most quantitative nonexperimental research, including what is called *causal-comparative* and *correlational* in education. On the other hand, Gay and Airasian (2000) seem to view survey research as including only descriptive studies. Because of the apparent overlap of survey research with some of the other categories used in education, Gall et al. (1996) and Johnson and Christensen (2000) treat surveys as a *method of data collection* rather than as a *research method*.

Development of a New Classification of Nonexperimental Research

The clearest way to classify nonexperimental quantitative research is based on the major or primary research objective. In other words, determine what the researcher is attempting to do in the research study. Studies can be usefully classified into the categories of *descriptive research*, *predictive research*, and *explanatory research*. To determine whether the primary objective

**Table 1. Nonexperimental Quantitative Research Classifications
From Leading Textbooks in Education and Related Fields**

Author	Types of nonexperimental quantitative research
Anthropology	
Bernard (1994)	Natural experiments
Education	
Ary, Jacobs, & Razavieh (1996)	Causal-comparative, correlational, & survey
Best & Kahn (1998)	Descriptive
Creswell (1994)	Survey
Crowl (1996)	Survey, correlational, group comparison
Fraenkel & Wallen (2000)	Correlational, causal-comparative, & survey
Gall, Borg, & Gall (1996)	Descriptive, causal-comparative, & correlational
Gay & Airasian (2000)	Descriptive, causal-comparative, & correlational
Krathwohl (1997)	Survey, after-the-fact natural experiments, ex post facto, causal comparison, & meta-analysis
McMillan & Schumacher (2000)	Descriptive, correlational, comparative, ex post facto, & survey
Slavin (1992)	Correlational & descriptive
Tuckman (1994)	Ex post facto
Vockell & Asher (1995)	Descriptive (status), criterion group, correlational, & meta-analysis
Wiersma (1995)	Survey
Education & related fields	
Cook & Campbell (1979)	Passive observation
Kerlinger & Lee (2000)	Nonexperimental & survey (i.e., explanatory survey)
Pedhazur & Schmelkin (1991)	Predictive & explanatory nonexperimental
Psychology	
Christensen (2001)	Correlational, ex post facto, longitudinal and cross-sectional, survey, & meta-analysis
Rosnow & Rosenthal (1993)	Descriptive & relational
Political science	
Frankfort-Nachmias & Nachmias (1999)	Cross-sectional, panels, & contrasted groups
Sociology	
Babbie (2001)	Survey, content analysis, & existing statistics
Neuman (1997)	Survey, nonreactive/content analysis, & available data
Singleton, Straits, & Straits (1999)	Survey & available data

was description, one needs to answer the following questions: (a) Were the researchers primarily describing the phenomenon? (b) Were the researchers documenting the characteristics of the phenomenon? If the answer is “yes” (and there is no manipulation) then the term *descriptive nonexperimental research* should be applied. To determine whether the primary objective was predictive, one needs to answer the following question: Did the researchers conduct the research so that they could predict or forecast some event or phenomenon in the future (without regard for cause and effect)? If the answer is “yes” (and there is no manipulation) then the term *predictive nonexperimental research* should be applied. To determine whether the primary objective was explanatory, one needs to answer the following questions: (a) Were the researchers trying to develop or test a theory about a phenomenon to explain “how” and “why” it operates? (b) Were the researchers trying to explain how the phenomenon operates by identifying the causal factors that produce change in it? If the answer is “yes” (and there is no manipulation) then the term *explanatory nonexperimental research* should be applied.

It is also helpful to classify nonexperimental quantitative research according to the time dimension. In other words, what kind of data did the researcher collect? Here the types of research include *cross-sectional research*, *longitudinal research*, and *retrospective research*. In cross-sectional research the data are collected from research participants at a single point in time or during a single, relatively brief time period (called contemporaneous measurement), the data directly apply to each case at that single time period, and comparisons are made across the variables of interest. In longitudinal research the data are collected at more than one time point or data collection period and the researcher makes comparisons across time (i.e., starting with the present and then collecting more data at a later time for comparison). Data can be collected on one or multiple groups in longitudinal research. Two subtypes of longitudinal research are *trend studies* (where independent samples are taken from a population over time and the same questions are asked) and *panel or prospective studies* (where the same individuals are studied at successive points over time). The panel or prospective study is an especially

important case when interest is in establishing evidence of causality because data on the independent and control variables can be obtained prior to the data on the dependent variable from the people in the panel. This helps to establish proper time order (i.e., Necessary Condition 2). In retrospective research, the researcher looks backward in time (typically starting with the dependent variable and moving backward in time to locate information on independent variables that help explain current differences on the dependent variable). In retrospective research, comparisons are made between the past (as estimated by the data) and the present for the cases in the data set. The researcher basically tries to simulate or approximate a longitudinal study (i.e., to obtain data representative of more than one time period).

The two dimensions just presented (research objective and time) provide important and meaningful information about the different forms nonexperimental research can take (Johnson & Christensen, 2000). Use of these terms will convey important information to readers of journal articles and other forms of professional communication because they more clearly delineate what was done in a specific research study. Notice that the two dimensions can be crossed, forming a 3-by-3 table and resulting in nine different types of nonexperimental research (see Table 2).

Several specific examples of the study types in Table 2 are mentioned here. First, in the article “Psychological Predictors of School-Based Violence: Implications for School Counselors” the researchers (Dykeman, Daehlin, Doyle, & Flamer, 1996) wanted to examine whether three psychological constructs could be used to predict violence among students in Grades 5 through 10. The psychological constructs were impulsivity, empathy, and locus of control. The data were collected at a single time point from 280 students (ages 10–19) with a self-report instrument. This study is an example of Type 5 because the research objective was predictive and the data were cross-sectional; it was a *cross-sectional, predictive research study*.

Another example is the study titled “A Prospective, Longitudinal Study of the Correlates and Consequences of Early Grade Retention” (Jimerson, Carlson, Rotert, Egeland, & Stroufe, 1997). The researchers in this study identified groups of retained students (32 children) and nonretained students (25 children) that were matched on several variables. Statistical controls were also used to help further equate the groups. All of the children were followed over time, with the data being collected when the children were in kindergarten, first grade, second grade, third grade,

sixth grade, and again at age 16. This study is an example of Type 9 because the research objective was explanatory (i.e., the researchers were interested in understanding the effects of retention) and the data were longitudinal (i.e., the data were collected at multiple time points); it was a *longitudinal, explanatory research study*.

A third example is the study titled “Perceived Teacher Support of Student Questioning in the College Classroom: Its Relation to Student Characteristics and Role in the Classroom Questioning Process” (Karabenick & Sharma, 1994). These researchers constructed a hypothesized causal or explanatory model of factors affecting students asking questions during lectures. The model included hypothesized direct and indirect effects. The researchers collected data from 1,327 students during a single time period (i.e., the data were cross-sectional) using a self-report instrument, and they analyzed the data using LISREL. This study is an example of Type 8 because the research objective was to test an explanatory model and the data were cross-sectional; it was a *cross-sectional, explanatory research study*.

A last example is the study titled “Tobacco Smoking as a Possible Etiologic Factor in Bronchogenic Carcinoma” (Wynder & Graham, 1950). In this classic study on smoking and lung cancer, the researchers collected data from 604 hospital patients with bronchiogenic carcinoma and 780 hospital patients without cancer. These groups were matched on several variables. The data were collected through interviews, and past smoking habits were estimated based on the patients’ responses to a set of retrospective questions (e.g., At what age did you begin to smoke? At what age did you stop smoking? How much tobacco did you average per day during the past 20 years of your smoking?) The researchers showed that patients with lung cancer were more likely to smoke than were the control patients and they were more likely to smoke excessively. The purpose of this study was to determine if the smoking of cigarettes was a possible cause of lung cancer. This is an example of Type 7 because the purpose was explanation (examining the possible causes of lung cancer) and the data were retrospective (in this case the data were based on retrospective questions rather than on past records); it was a *retrospective, explanatory research study*.

A potential weakness of the typology shown in Table 2 is that it may be difficult to remember nine different types of nonexperimental quantitative research. A solution is to simply memorize the three major categories for the *research objective dimension* (i.e., descriptive, predictive, and explanatory) and the three major categories for the *time dimension* (i.e., retrospective, cross-sectional, and longitudinal). One needs to answer two questions:

Table 2. Types of Research Obtained by Crossing Research Objective and Time Dimension

Research objective	Time dimension		
	Retrospective	Cross-sectional	Longitudinal
Descriptive	Retrospective, descriptive study (Type 1)	Cross-sectional, descriptive study (Type 2)	Longitudinal, descriptive study (Type 3)
Predictive	Retrospective, predictive study (Type 4)	Cross-sectional, predictive study (Type 5)	Longitudinal, predictive study (Type 6)
Explanatory	Retrospective, explanatory study (Type 7)	Cross-sectional, explanatory study (Type 8)	Longitudinal, explanatory study (Type 9)

(a) What was the primary research objective? and (b) Where does the study fall on the time dimension? One needs to answer these two questions and then present this important information in the method section of the research report. Of course the terms can also be combined into slightly complex names, such as a *cross-sectional, descriptive study* and a *longitudinal, explanatory study*.

The nonexperimental research typology presented in Table 2 also has three key strengths. The first strength is that, unlike the presentations in most educational research books (e.g., Fraenkel & Wallen, 2000; Gall et al., 1996; Gay & Airasian, 2000), all of the types of nonexperimental research shown in Table 2 are included in a single and systematically generated typology. For example, the authors of Gay and Airasian (2000) do not present a single typology showing the major and subtypes of nonexperimental quantitative research. In one chapter, four types of descriptive (nonexperimental) research are listed: *trend survey, cohort survey, panel survey, and follow-up survey*. In another chapter, two types of correlational (nonexperimental) research are listed: *relationship studies* and *prediction studies*. In a chapter on causal-comparative (nonexperimental) research, two more types are listed: *prospective causal-comparative* and *retrospective causal-comparative* research studies. In contrast, the single typology shown in Table 2 is clearly the result of the systematic, cross-classification of two meaningful dimensions (i.e., research purpose and time).

The second strength of the typology in Table 2 is that the nine types of nonexperimental quantitative research are *mutually exclusive*. This was not the case for several of the typologies shown in Table 1. For example, some of what Fraenkel and Wallen (2000) call *survey research* could easily be called *correlational research* (if the data were collected through questionnaires or interviews) and some of what Gay and Airasian (2000) call *descriptive research* would be placed in the *correlational research* category by many observers. Finally, a study that is a mix between what Gay and Airasian call *correlational* and *causal-comparative* would imperfectly fit in either category (e.g., a structural equation model that is done for two different groups or a regression-based model where one has two key independent variables, one that is categorical and one that is quantitative).

The third strength of the typology in Table 2 is that the nine types of nonexperimental quantitative research are *exhaustive*. Although each author whose typology is shown in Table 1 likely believes his or her typology is exhaustive, this seems to be a questionable assumption when one looks at all of the typologies. For example, wouldn't Best and Kahn's (1998) category of *descriptive research* have to exclude some nonexperimental quantitative research in which the purpose is either predictive or explanatory? What about Creswell's (1994) single category of *survey research* or Tuckman's (1994) single category of *ex post facto research*? Where would Gay and Airasian classify an explanatory survey research study if all survey studies are assumed to be descriptive?

These strengths can be seen by trying to classify a study involving a structural equation model based on nonexperimental cross-sectional data. (This is the most frequently occurring structural equation model in education and other fields.) In the classification shown in Table 2 it would be a *cross-sectional, explanatory study* because the data are cross-sectional and the purpose is to test a theoretical model (i.e., explanation). This is the kind of information that would need to be included in the description of

the study regardless of what research typology and research descriptor one uses. Therefore, why not simply use a typology based on these important dimensions, rather than defining terms such as *correlational research, survey research, and causal-comparative research*, and their subtypes, in somewhat idiosyncratic ways as is currently done? The structural equation modeling study just mentioned would be called a *correlational* research study by Fraenkel and Wallen (2000). Smith and Glass (1987) would call it a *causal-comparative* research study. Other authors would probably classify it as *survey research* (e.g., Babbie, 2001; Creswell, 1994; Wiesner, 1995) if the data were collected through questionnaires or interviews. No wonder we sometimes find it difficult to communicate with one another!

Conclusion

Educational researchers currently participate in an increasingly interdisciplinary environment, and it is important that we use terminology and research classifications that are defensible and make sense to researchers in education and related fields (e.g., psychology, sociology, political science, anthropology, nursing, business). One problem is that outside of education, virtually no one has heard of *causal-comparative* research (e.g., see Babbie, 2001; Checkoway, Pearce, & Crawford-Brown, 1989; Christensen, 2001; Davis & Cosena, 1993; Frankfort-Nachmias & Nachmias, 1999; Jones, 1995; Judd et al., 1991; LoBiondo-Wood & Haber, 1994; Neuman, 1997; Malhotra, 1993; Pedhazur & Schmelkin, 1991; Singleton, Straite, & Straits, 1999). Other problems are that the terms *causal-comparative* and *correlational* refer to very similar approaches, they are inconsistently defined and treated in current textbooks, they have been defined differently over time, and the two terms ultimately suggest a false dichotomy as they are presented in popular educational research texts (e.g., Charles, 1998; Gay & Airasian, 2000; Martella et al., 1999). A solution is to use a newer and more logical classification of nonexperimental quantitative research. Virtually all researchers know the difference between description, prediction, and explanation, and they know the difference between cross-sectional data, longitudinal data, and retrospective data. These two dimensions make up the nonexperimental research typology developed in this paper. This typology should be useful in education as well as in related disciplines.

NOTES

¹ I do not address the interesting topic of causality in *qualitative* research in this paper.

² This quote is from the third, non-numbered page of Gay & Airasian (2000).

³ A lively and extensive discussion took place on the AERA Division-D Internet Discussion Group, spanning several weeks, about the relative strengths of causal-comparative and correlational research. The archives of the discussion can be accessed from the AERA webpage or at <http://lists.asu.edu/archives/aerad.html>. A total of 70 messages were posted in this discussion which began with a message posted by Burke Johnson on February 6, 1998, and ended with a message posted by Michael Scriven on March 5, 1998. The discussion took place under several headings including "research methods question," "causal-comparative vs. correlational," "causal-comparative and cause," "Professor Johnson," "the correlation/causal-comparative controversy," "correlational/C-C questionnaire," and "10 reasons causal-comparative is better than correlational."

⁴ The early writers were, perhaps, overly optimistic about the power of statistical techniques for control. For example, partial effects are difficult to interpret in the presence of random measurement error for predictor variables (e.g., Cook & Campbell, 1979, pp. 157–164; also see Thompson, 1992).

⁵ Although the simple causal-comparative design looks much like the weak or pre-experimental “static group comparison” design (i.e., both designs compare groups and neither has a pretest), the simple causal-comparative design has even less going for it than the static group design in that the independent variable is not manipulated.

⁶ If, given the context, it might be unclear to a reader that the non-experimental study being described is a *quantitative* study, then use the full term “nonexperimental *quantitative* research” rather than the shorter term “nonexperimental research.”

⁷ Donald Campbell also dropped the term *ex post facto* (cf. Campbell & Stanley, 1963; Cook & Campbell, 1979).

⁸ The practice of categorizing quantitatively scaled variables may have developed prior to the widespread use of computers as a result of the ease of mathematical computations in ANOVA (Tatsuoka, 1993).

REFERENCES

- Allyn & Bacon. (1996). *A&B research methods survey*. Boston: Author.
- Ary, D., Jacobs, L. C., & Razavieh, A. (1996). *Introduction to research in education* (5th ed.). Fort Worth, TX: Harcourt Brace.
- Babbie, E. (2001). *The practice of social research* (9th ed.). Belmont, CA: Wadsworth.
- Bernard, H. R. (1994). *Research methods in anthropology: Qualitative and quantitative approaches* (2nd ed.). Thousand Oaks, CA: Sage.
- Best, J. W., & Kahn, J. V. (1998). *Research in education* (8th ed.). Boston: Allyn and Bacon.
- Blalock, H. M. (1964). *Causal inference in nonexperimental research*. New York: Norton.
- Bollen, K. A. (1989). *Structural equations with latent variables*. New York: Wiley.
- Campbell, D. T., & Stanley, J. C. (1963). *Experimental and quasi-experimental designs for research*. Chicago: Rand McNally.
- Charles, C. M. (1998). *Introduction to educational research* (2nd ed.). White Plains, NY: Longman.
- Checkoway, H., Pearce, N., & Crawford-Brown, D. L. (1989). *Research methods in occupational epidemiology*. New York: Oxford.
- Christensen, L. B. (2001). *Experimental methodology* (8th ed.). Boston: Allyn and Bacon.
- Cohen, J., & Cohen, P. (1983). *Applied multiple regression/correlation analysis for the behavioral sciences* (2nd ed.). New York: Wiley.
- Cook, T. D., & Campbell, D. T. (1979). *Quasi-experimentation: Design and analysis issues for field settings*. Chicago: Rand McNally.
- Cordray, D. S. (1990). Strengthening causal interpretations of non-experimental data: The role of meta-analysis. In L. Sechrest, E. Perrin, & J. Bunker (Eds.), *Research methodology: Strengthening causal interpretations of nonexperimental data* (pp. 151–172). Washington, DC: U.S. Department of Health and Human Resources.
- Creswell, J. W. (1994). *Research design: Qualitative and quantitative approaches*. Thousand Oaks, CA: Sage.
- Crowl, T. K. (1996). *Fundamentals of educational research* (2nd ed.). Madison, WI: Brown & Benchmark.
- Davis, D., & Cosena, R. M. (1993). *Business research for decision making* (3rd ed.). Belmont, CA: Wadsworth.
- Davis, J. A. (1985). *The logic of causal order*. Beverly Hills, CA: Sage.
- Denzin, N. K. (1989). *The research act: A theoretical introduction to sociological methods* (3rd ed.). Englewood Cliffs, NJ: Prentice Hall.
- Dykeman, C., Daehlin, W., Doyle, S., & Flamer, H. S. (1996). Psychological predictors of school-based violence: Implications for school counselors. *The School Counselor*, 44, 35–44.
- Fraenkel, J. R., & Wallen, N. E. (2000). *How to design and evaluate research in education* (4th ed.). New York: McGraw-Hill.
- Frankfort-Nachmias, C., & Nachmias, D. (1999). *Research methods in the social sciences* (6th ed.). New York: St. Martin's.
- Gall, M. D., Borg, W. R., & Gall, J. P. (1996). *Educational research: An introduction* (6th ed.). White Plains, NY: Longman.
- Gay, L. R., & Airasian, P. (2000). *Educational research: Competencies for analysis and application* (6th ed.). Englewood Cliffs, NJ: Prentice-Hall.
- Good, C. V., Barr, A. S., & Scates, D. E. (1935). *The methodology of educational research*. New York: Appleton-Century-Crofts.
- Huck, S. W., & Sandler, H. M. (1979). *Rival hypotheses: Alternative interpretation of data based conclusions*. New York: Harper and Row.
- Jimerson, S., Carlson, E., Rotert, M., Egeland, B., & Sroufe, L. A. (1997). A prospective, longitudinal study of the correlates and consequences of early grade retention. *Journal of School Psychology*, 35(1), 3–25.
- Johnson, R. B., & Christensen, L. B. (2000). *Educational research: Quantitative and qualitative approaches*. Boston: Allyn and Bacon.
- Jones, J. L. (1995). *Understanding psychological science*. New York: Harper Collins.
- Judd, C. M., Smith, E. R., & Kidder, L. H. (1991). *Research methods in social relations* (6th ed.). Fort Worth, TX: Harcourt Brace Jovanovich.
- Karabenick, S. A., & Sharma, R. (1994). Perceived teacher support of student questioning in the college classroom: Its relation to student characteristics and role in the classroom questioning process. *Journal of Educational Psychology*, 86(1), 90–103.
- Kerlinger, F. N. (1973). *Foundations of behavioral research* (2nd ed.). New York: Holt, Rinehart & Winston.
- Kerlinger, F. N. (1986). *Foundations of behavioral research* (3rd ed.). New York: Holt, Rinehart & Winston.
- Kerlinger, F. N., & Lee, H. B. (2000). *Foundations of behavioral research* (4th ed.). Fort Worth, TX: Harcourt.
- Knapp, T. R. (1978). Canonical correlation analysis: A general parametric significance testing system. *Psychological Bulletin*, 85, 410–416.
- Krathwohl, D. R. (1997). *Methods of educational and social science research: An integrated approach* (2nd ed.). White Plains, NY: Longman.
- Lancaster, B. P. (1999). Defining and interpreting suppressor effects: Advantages and limitations. In B. Thompson (Ed.), *Advances in social science methodology* (pp. 139–148). Stamford, CT: JAI Press.
- LoBiondo-Wood, G., & Haber, J. (1994). *Nursing research* (3rd ed.). St Louis, MO: Mosby.
- Malhotra, N. K. (1993). *Marketing research: An applied orientation*. Englewood Cliffs, NJ: Prentice Hall.
- Martella, R. C., Nelson, R., & Marchand-Martella, N. E. (1999). *Research methods: Learning to become a critical research consumer*. Boston: Allyn and Bacon.
- Maruyama, G. M. (1998). *Basics of structural equation modeling*. Thousand Oaks, CA: Sage.
- McMillan, J. H., & Schumacher, S. (2000). *Research in education: A conceptual introduction* (5th ed.). New York: Addison-Wesley.
- McNeil, K., Newman, I., & Kelly, F. J. (1996). *Testing research hypotheses with the general linear model*. Carbondale, IL: Southern Illinois University Press.
- Moore, D. S., & McCabe, G. P. (1998). *Introduction to the practice of statistics* (3rd ed.). New York: W.H. Freeman.
- Neuman, W. L. (1997). *Social research methods* (3rd ed.). Boston: Allyn and Bacon.
- Pedhazur, E. J. (1997). *Multiple regression in behavioral research: Explanation and prediction* (3rd ed.). New York: Holt, Rinehart & Winston.
- Pedhazur, E. J., & Schmelkin, L. P. (1991). *Measurement, design, and analysis: An integrated approach*. Hillsdale, NJ: Lawrence Erlbaum.
- Popper, K. R. (1959). *The logic of scientific discovery*. New York: Basic Books.

- Rindskopf, D. (1992). The importance of theory in selection modeling: Incorrect assumptions mean biased results. In H. Chen & P. H. Rossi (Eds.), *Using theory to improve program and policy evaluations* (pp. 179–191). New York: Greenwood Press.
- Rosnow, R. L., & Rosenthal, R. (1993). *Beginning behavioral research: A conceptual primer*. New York: Macmillan.
- Rossi, P. H., Freeman, H. E., & Lipsey, M. W. (1999). *Evaluation: A systematic approach* (6th ed.). Thousand Oaks, CA: Sage.
- Singleton, R. A., Straits, B. C., & Straits, M. M. (1999). *Approaches to social research* (3rd ed.). New York: Oxford.
- Slavin, R.E. (1992). *Research methods in education* (2nd ed.). Boston: Allyn and Bacon.
- Smith, M. L., & Glass, G. V. (1987). *Research and evaluation in education and the social sciences*. Boston: Allyn and Bacon.
- Tashakkori, A., & Teddlie, C. (1998). *Mixed methodology: Combining qualitative and quantitative approaches*. Thousand Oaks, CA: Sage.
- Tatsuoka, M. (1993). Elements of the general linear model. In G. Keren & C. Lewis (Eds.), *Data analysis in the behavioral sciences* (pp. 3–41). Hillsdale, NJ: Lawrence Erlbaum.
- Thompson, B. (1992). Misuse of ANCOVA and related “statistical control” procedures. *Reading Psychology: An International Quarterly*, 13, iii–xvii.
- Thompson, B. (1999). Five methodology errors in educational research: The pantheon of statistical significance and other faux pas. In B. Thompson (Ed.), *Advances in social science methodology* (pp. 23–86). Stamford, CT: JAI Press.
- Trochim, W. (1989). Outcome pattern matching and program theory. *Evaluation and Program Planning*, 12(4), 355–366.
- Tuckman, B. W. (1994). *Conducting educational research*. Fort Worth, TX: Harcourt Brace.
- Vockell, E. L., & Asher, J. W. (1995). *Educational research* (2nd ed.). Englewood Cliffs, NJ: Merrill.
- Wiersma, W. (1995). *Research methods in education: An introduction* (6th ed.). Boston: Allyn and Bacon.
- Wynder, E. L., & Graham, E. A. (1950). Tobacco smoking as a possible etiologic factor in bronchogenic carcinoma. *Journal of the American Medical Association*, 143, 329–336.
- Yin, R. K. (2000). Rival explanations as an alternative to reforms as experiments. In L. Bickman (Ed.), *Validity and social experimentation* (pp. 239–266). Thousand Oaks, CA: Sage.

AUTHOR

BURKE JOHNSON is Associate Professor at the College of Education, BSET, University of South Alabama, 3700 UCOM, Mobile, AL 36688; e-mail bjohnson@usamail.usouthal.edu. He specializes in research methodology.

Manuscript received September 5, 2000

Revisions received November 8, 2000, December 21, 2000

Accepted December 27, 2000