PART I

Conceptual Foundations of the Elaboration Model

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Introduction to Theory-Based Data Analysis

Quantitative data analysis is as much a logical enterprise as it is a statistical one. Although few social scientists would debate this point, contemporary research often emphasizes statistical technique at the expense of logical discourse. This is not to say that the analyses are illogical but rather that the connection of statistics to theory is often haphazard. This situation has developed to a large degree from the ease with which complex and powerful statistical models can be estimated in today's computer-dominated research environment. For this reason, it is likely to become even more pronounced as these tools become all the more accessible. In this text, I offer an alternative that emphasizes the role of theory.

Theory-based data analysis entails movement back and forth between the theoretical realm and the empirical one. A social science **theory** is a coherent set of general principles connected to each other by logical arguments that proposes an explanation for a phenomenon. In other words, it is a system of ideas that provides a plausible and rational description of cause-and-effect type relationships among a set constructs.[1] Theory-based data analysis tests this explanation. Based on the results of this analysis, the theory is supported or refuted, and this information is used to refine, reformulate, or reject the theory. In this manner, theory directs data analysis, while the results of that analysis shape the next permutation of the theory in a self-reinforcing cycle that ideally leads to the accumulation of knowledge about the phenomenon under investigation.

After introducing key concepts in theory-based data analysis, this chapter discusses explanatory analysis and presents an overview of the elaboration model—the method of data analysis that is presented in this text—followed by a recent study of boundary-spanning work demands that illustrate its application. The chapter then describes the connections among theory, statistics, and data analysis. It concludes with a brief discussion of the inherent subjectivity of analysis, even in its most quantitative and seemingly objective forms. These closing remarks strike a cautionary note: Data analysis provides insight into the workings of the social world, but this vision inevitably is shaped and constrained by our most fundamental assumptions about the nature of the social world—assumptions so basic that they often are imperceptible.

Key Concepts of Theory-Based Data Analysis

Data and Data Analysis

The term **data** refers to a body of raw or unorganized information that has been collected together for the purpose of analysis, drawing conclusions, or making decisions. It includes facts (e.g., date of birth, infant mortality rate), events (e.g., birth of a child, natural disaster), things (e.g., home ownership, gross national product), ideas (e.g., religious beliefs, political ideology), and so forth. Data consist of symbols for this information. In quantitative data, numerical representations are used. For example, for the following statement, "Some people can make me aware of them just by thinking about me," an indicator of magical thinking (Eckblad & Chapman, 1983), the responses of false and true could be coded 0 and 1, respectively.

Data do not have intrinsic meaning. By itself, a set of data is just an accumulation of numbers signifying bits and pieces of information. Its nature must be comprehended. This understanding is accomplished through **data analysis**, which is the systematic arrangement of information into intelligible patterns. In other words, data analysis refers to the process of investigating data in order to make sense of it. Analysis typically entails separating a phenomenon into its constituent elements to study its nature, but the elaboration model of data analysis presented in this text places equal emphasis on synthesis, combining those elements into a complex, unified whole.

In the words of Rosenberg (1968), analysis is the "dynamic interplay between theory and data" (p. 217). Theory describes an imaginary world. The existence of this world is inferred from observations of the phenomenon under investigation that are made in the empirical or "real" world. In the theory-generating phase of social research, the essence of these observations is abstracted and conceptually interpreted to formulate an explanation for the phenomenon—ideas about its nature, antecedents, and consequences. In the theory-testing phase, these ideas are translated into **hypotheses**, which are statements about what one expects to find if the theory is correct—statements that are capable of being shown to be false. Then the theory is tested by making new observations and ascertaining whether the resultant data are consistent with these observations.

Contrary to what is often taught in introductory methods courses, this process is not just one of rejecting or failing to reject a hypothesis. Rather, affirmative findings are used to develop and refine the theory, whereas negative ones prompt a reconsideration of all aspects of the theory, which is just as likely to lead to it being reformulated as to it being abandoned. In this manner, data analysis modifies theory as much as theory directs analysis. For these reasons, Barnes, Bloor, and Henry (1996) maintain that "the interaction of theory and observation reports may be regarded as an interaction between past observations [condensed in theory], and present observations [reported as such]. If observation is 'theory laden', theory is 'observation laden'" (p. 92).

Data analysis does not begin on a tabula rasa at the end of data collection. Rather, the analysis plan is formulated during the design of the study, when the theory guiding the research is translated into a set of research questions and hypotheses and into a set of procedures that eventually generate the data to be analyzed. The form and character of what one seeks to uncover from a set of data, therefore, are known at the outset. Research questions and hypotheses more often than not evolve as the analysis proceeds, sometimes undergoing metamorphosis, but the original theoretical framework establishes the starting point for this journey of discovery.[2]

Constructs and Measured Variables

For theory-based data analysis in the social sciences, the celestial realm of theory concerns hypothesized relationships among constructs in a population. The earthly empirical realm is its mirror image: estimating associations among measured variables in a sample. A **construct** is a mental image of things that do not actually exist in a tangible form, an abstract representation of a general class of immaterial things, circumstances, and occurrences, such as social support, disadvantaged neighborhoods, and academic success. It signifies the essence of the idea and the particular combination of qualities that define it.

As an example, contemporary personality theory posits five "big" domains: (1) extraversion, (2) openness, (3) conscientiousness, (4) agreeableness, and (5) neuroticism. Although the idea of personality is widely understood in contemporary Western society, these qualities are not real; they are social constructions, a term that refers to meanings that are socially (as distinct from personally) attributed to things, facts, practices, and so forth. The existence of personality traits is inferred from seeing how a person behaves, especially the extent to which his or her behavior endures over time, is consistent across various settings, and, hence, is understood to be indicative of some underlying disposition.

As a case in point, the construct of neuroticism refers to a persistent tendency to experience negative emotional states, such as anxiety, anger, irritability, or depressed mood. Neuroticism entails extreme emotional reactivity to environmental stress, including events that would not affect most people; ordinary situations are interpreted as threatening, and minor frustrations are experienced as overwhelming difficulties. At the other end of the continuum is the tendency to be calm, less emotionally reactive, and relatively free from negative feelings. The idea of personality is so familiar as to be taken for granted, yet the existence of a trait like neuroticism is not factual, it is a customary way of thinking about the ways in which people usually think, feel, and act.

A construct is by its very nature intangible and cannot be experienced through direct perception but instead is known through its manifestations. In research, these manifestations are known as **measured variables**, which are the concrete empirical assessments of constructs. A **variable** is a characteristic that can have different values across the units of observation for a study (e.g., people in a sample differ in their level of neuroticism).

To illustrate this point, one measure of the personality trait of neuroticism is the Mini-IPIP (Donnellan, Oswald, Baird, & Lucas, 2006), a 20-item version of the more comprehensive 50-item International Personality Item Pool (IPIP) five-factor model measure, which contains 4 items assessing this construct (the other 16 items assess the other 4 personality factors). The neuroticism items are "have frequent mood swings," "am relaxed most of the time" (R), "get upset easily," and "seldom feel blue" (R). Respondents are asked to rate how much these statements describe themselves with response options of (1) "very inaccurate" through (3) "neither inaccurate nor accurate" to (5) "very accurate"; items marked R are scored in the reverse direction (e.g., 5 = "very inaccurate"), and responses are averaged across items, with the highest score indicating the most neuroticism. These scores constitute the measured variable that corresponds to the theoretical trait of neuroticism. For a large sample of undergraduates, the average response is midway between "moderately inaccurate" and "neither inaccurate nor accurate" a generally low level of neuroticism, but there is considerable variability, and some students endorse most if not all of these characteristics (Donnellan et al., 2006).

The analysis of a construct almost always begins with an assessment of how well it has been measured. This analysis involves both an assessment of **reliability**, which is the extent to which measurement can be reproduced, and an evaluation of **content validity**, which is how well a measure corresponds to the theoretical definition of a construct. The latter is essential to the integrity of the entire enterprise because the connection of the variable to other variables is meaningless if the measured variable is a poor proxy for the construct and if, for example, it measures anxiety rather than neuroticism. Reliability is a prerequisite for validity: A measure inherently lacks validity if it cannot be duplicated.

However, even the most reliable and valid measures are imperfect approximations of constructs. The deviation between the true value of the construct and the measured value is referred to as **measurement error**. This slippage is extremely consequential to the assessment of relationships among constructs, as discussed in Chapter 2.

Relationships and Associations

Social science theory typically seeks to explain the occurrence of the phenomena under investigation and does so by positing causal relationships among constructs that are estimated as associations among measured variables. **Association** is present when the values on the variables tend to coincide with one another, whereas **relationship** additionally implies that one construct influences another construct in a causal manner. This leads us to distinguish two types of variables: (1) the **independent variable**, the variable in a relationship whose value is thought to determine the value of another variable, and (2) the **dependent variable**, the variable whose values are determined.[3] The results of the empirical test of the association are used to draw conclusions about the theoretical relationship. In this manner, data analysis is the Rosetta Stone that enables us to move back and forth between the theoretical and empirical realms.

For example, the hypothesis that personality affects academic performance was tested in a recent study of college undergraduates from diverse socioeconomic and racial/ethnic backgrounds using four different personality inventories (Noftle & Robins, 2007). The analytic results show that the independent variable of neuroticism is for all intents and purposes *not* associated with the dependent variables of academic ability or academic performance as indexed by Scholastic Aptitude Test (SAT) scores and grade point average (GPA) in high school or college, respectively. However, the same study finds that both SAT scores and

GPA are associated with the personality trait of conscientiousness, which refers to being meticulous, responsible, deliberate, and self-disciplined with good impulse control and goal-directed behaviors.

The inference that this association represents a relationship is supported by findings that are consistent with the hypothesized causal mechanisms that link this personality trait to academic success: higher levels of academic effort and perceived academic ability (Noftle & Robins, 2007). In other words, people who are conscientious have better grades in college than their otherwise comparable classmates, at least in part, because they see themselves as having the ability to do well and work hard to actualize that potential. This explanation supports the theory guiding this research, namely, that personality influences academic achievement independent of intelligence or other aspects of cognitive ability.

Populations and Samples

In addition, most social science research seeks to generalize results from a sample to some larger population. A **population** is the entire set of all units constituting a particular collection of units of that type, also called a **universe**. In social science research, the units often are people, such as adults in the United States, or aggregations of people, such as neighborhoods in a city.[4] Populations usually are not studied in their entirety but with a **sample**, which is a subset of the population—a miniature version of it. Although some populations are self-contained with clear boundaries, for example, all children in a particular school, social science research more often than not concerns general populations that are not capable of being studied exhaustively because they are too large, their boundaries are unknown, or enumerating them is not possible. To illustrate this point, the U.S. population changes before it can be completely counted even in the decennial Census because births, deaths, and immigration continuously and instantaneously alter its composition. Also, it is almost always prohibitively expensive to study the entire population and unnecessary as well because data from a sample are sufficient to answer the research question.

Consequently, samples are used as surrogates for populations in the same manner that measured variables stand in for constructs and associations serve as proxies for relationships. For example, the study of personality and academic achievement just described used several samples of college undergraduates to draw conclusions about college undergraduates in general. These samples typically, although not always, are **probability samples**, which are samples that use a random mechanism of selection so that every unit has a known chance of being selected for the sample.[5]

The association between two measured variables has a known exact value in the sample, but we are interested in that value primarily as an estimate of the true value in the population, which is known as a **parameter**. This projection necessitates the application of **inferential statistics**, which is the use of probability theory for inferring the properties of a population from a sample. This is the subject matter of introductory statistics courses and should be familiar. Theory-based data analysis rests on this foundation. Here it suffices to say that use of sample data to make inferences about the population means that we cannot entirely rule out the possibility that our findings are due to chance. This uncertainty pertains to both findings that support the theory being tested and to those that refute it. It follows that our conclusions always are provisional.

Explanatory Data Analysis

Social science research in general and data analysis in particular may have exploratory, descriptive, or explanatory objectives or some combination of these aims.[6] Exploratory research generally is undertaken when very little is known about a phenomenon. It forms the foundation for subsequent descriptive and explanatory research. Descriptive research makes a valuable contribution to science. It serves to identify important areas of inquiry, addressing whether a phenomenon is a common occurrence or a rare event. For example, this type of research could be used to describe the pool of eligible voters for national elections, the extent to which these persons are registered to vote, and their voting behavior in recent elections. A survey like this would reveal a low rate of voter turnout in national elections, about 50% in years with presidential contests and less in off years, a finding indicating that voter turnout is worthy of further scientific investigation given that this form of civic participation is an essential aspect of a democratic society.

Scientific inquiry usually does not end with description, however, but proceeds almost immediately to explanation. Establishing the existence of a phenomenon more often than not stimulates curiosity about why that phenomenon exists. For example, once the extent of voter turnout is known, one is likely to ask whether certain subgroups are more likely to vote than are others and, if so, why. Wolfinger and Wolfinger (2008) find that married persons are most likely to vote, irrespective of their demographic characteristics, which the authors attribute to spousal encouragement and shared influences. They also reason that single parents, who are least likely to vote, abstain because it is a low priority for people struggling to cope with the demands of life as a single parent. Ironically, the authors point out that this vulnerable group may receive less representation from policymakers because they are light voters even though they need more of it. Although the relationship of marital status to voter turnout behavior is well documented in this study, the explanations offered for these differences were speculative, opening the door for subsequent research to test these mechanisms. In this manner, descriptive findings are likely to lead to the investigation of the factors that contribute to the occurrence of the outcome and its consequences. Thus, the search for scientific understanding tends to evolve in the direction of explanation.

Given this explanatory focus, a basic goal of most quantitative data analysis in the social sciences is to ascertain whether an empirical association between two measured variables can be interpreted as a relationship among the corresponding constructs, which means that the two constructs share a causative connection to one another, specifically that one construct influences the other. For example, one might test whether the demands of single parenthood do indeed account for the lower level of voter turnout among this group compared with married persons as hypothesized.

Theory-based data analysis in the social sciences generally seeks to test causal relationships among constructs, although this objective may not be explicit because of concerns about drawing causal inferences from observational data (see Chapter 4 for a discussion of causal inference in the social sciences). The core issue is one of **internal validity**—the extent to which conclusions about cause and effect can be drawn from the research (Cook & Campbell, 1979). In experimental research, internal validity is achieved through design, and as a result, this method provides the strongest basis for drawing inferences about causality. But many social science research questions are more appropriately addressed with studies of the phenomenon as it naturally occurs among the general population. In this instance, internal validity is achieved in large part through analysis.[7]

As just mentioned, constructs cannot be experienced firsthand because they are abstractions; for this reason, it is not possible to perceive directly relationships among them either. Quite the opposite, associations among the measured variables representing the constructs are estimated as surrogates for relationships among the corresponding constructs. The analytic task then becomes assessing the extent to which it is reasonable to interpret these associations as relationships.

Bearing on this point, Rosenberg (1968) argues that the introduction of **test factors** or "**third variables**," which are variables that are added to the analysis of an association between two other variables to clarify the nature of that association, enables us to exploit some of the virtues of the experimental design while avoiding the inappropriateness of experimentation for many research questions. To this end, this text describes the **elaboration model**—a method of data analysis for explicating the theoretical interpretation of an empirical association between two variables by systematically introducing additional third variables into the analysis.

Elements of the Elaboration Model of Theory-Based Data Analysis

The Elaboration Model

Data analysis has not always relied so exclusively on statistics. Survey research, for example, has a rich tradition that clearly articulates the logic of analysis. Influential in this tradition is Morris Rosenberg's (1968) classic, *The Logic of Survey Analysis*, describing the elaboration model for the analysis of survey data—originally developed by Paul Lazarsfeld. Rosenberg elegantly delineated the logical structure of the inferential analysis of such data. Unfortunately, the statistics and illustrations in the book are now dated, and hence, it is not read as widely nor appreciated as fully as it merits. Most textbook discussions of the elaboration model limit its application to cross-tabular analytic techniques for simple three-variable models. Although this application may be useful for pedagogical purposes, it is of limited value to students whose own research employs a broad array of variables in one simultaneous multivariate model. Nonetheless, the elaboration model contains the basic elements necessary for the logical analysis of observational data.

The elaboration model is an explanatory model. Its purpose is to account for an empirical association between two variables in order to explain why one variable is correlated with another. Although it has some utility in other applications, its power is realized most in instances in which cause and effect is an issue. Although there are other strategies for the theoretically meaningful analysis of quantitative data, the elaboration model is especially well suited to this task. Its advantages, therefore, are realized best in explanatory research.

It is useful to outline key aspects of the elaboration model now because it forms the foundation for the multivariate analytic strategy presented in this volume. The core issue in the elaboration model is whether an empirical association between two variables—one designated as the independent variable and the other as the dependent variable—represents a relationship, that is, whether it involves a causal connection between two variables.[8] In other words, does the independent variable influence the dependent variable in the manner envisioned by theory? Answering this question entails focusing attention on the association between these two variables and evaluating how it changes as additional variables are systematically introduced into the analysis.

Third Variables

Third variables or test factors are variables that are methodically added to an analysis to shed light on the nature of an association between two other variables. They are used to rule out alternative explanations for the observed association. For example, third variables are used to limit the possibility that the association merely reflects the mutual dependence of both variables on a common cause. They are also used to delineate the hypothesized causal mechanisms that produce the association between the other two variables. As we shall see, placing this association within a theory-based system of interlocking variables strengthens the inference that one variable is related to the other. Some third variables are used to ascertain whether an association is universal or is specific to particular conditions or social groups. This type of specification also can enhance the interpretation of an association as a relationship to the extent that these contingencies are consistent with theory.

Demonstrating that a hypothesized causal mechanism is feasible, while also ruling out alternative explanations for an empirical association, constitutes strong evidence for inferring that the association may represent a cause-and-effect type of relationship. These two functions of third variables—excluding alternative explanations and including explanatory variables—are the basis for the data analysis strategy described in this text.

Establishing relatedness necessitates multivariate analysis. Bivariate analysis is an essential first step, but it only tests whether the hypothesized association exists and exists at a level beyond that expected by chance. To demonstrate that this association can be interpreted legitimately as a cause-and-effect type of relationship, the model needs to be expanded to include at least one additional variable. This third variable is needed to rule out alternative interpretations or to test the causal mechanisms described by theory. In most applications, numerous third variables are included in the analysis using multivariate statistical techniques, such as those described in this text.

Although the assessment of relationship requires multivariate analysis, the application of multivariate statistical techniques sometimes inadvertently obscures the assessment of relatedness, as explained below. This paradoxical situation results from the large number of independent variables used in most analyses, which diverts attention away from the interpretation of any one independent variable as affecting the dependent variable.

The Focal Relationship

To counterbalance this practice, I use the notion of a **focal relationship**: the one relationship between an independent and a dependent variable that is central to the theory being applied in a particular study.[9] This single relationship becomes the cornerstone for the entire analytic strategy. This emphasis on one relationship does not imply that the theory itself is limited to this one relationship; on the contrary, most social science theories are multifactorial, detailing several influences on the dependent variable. It is precisely these multiple strands of explanation that make the idea of a focal relationship so useful. These multiple strands often compete for equal attention during analysis so that the result is unfocused; this situation can result in a suboptimal test of the theory. In particular, the analyses may overlook those that would substantiate any inference of causality.

Organizing the empirical test of a theory in a single study around one focal relationship often provides a more effective approach to testing that theory than giving equal weight to multiple relationships because the one relationship can be systematically subjected to multiple tests of alternative explanations, and confidence in the inference of relatedness increases in proportion to the number of alternative explanations that do not disconfirm it. In addition, the other relationships that comprise the theory model can be used strategically to ascertain that this one relationship fits within a network of other relationships, which also enhances the inference that it is a relationship.

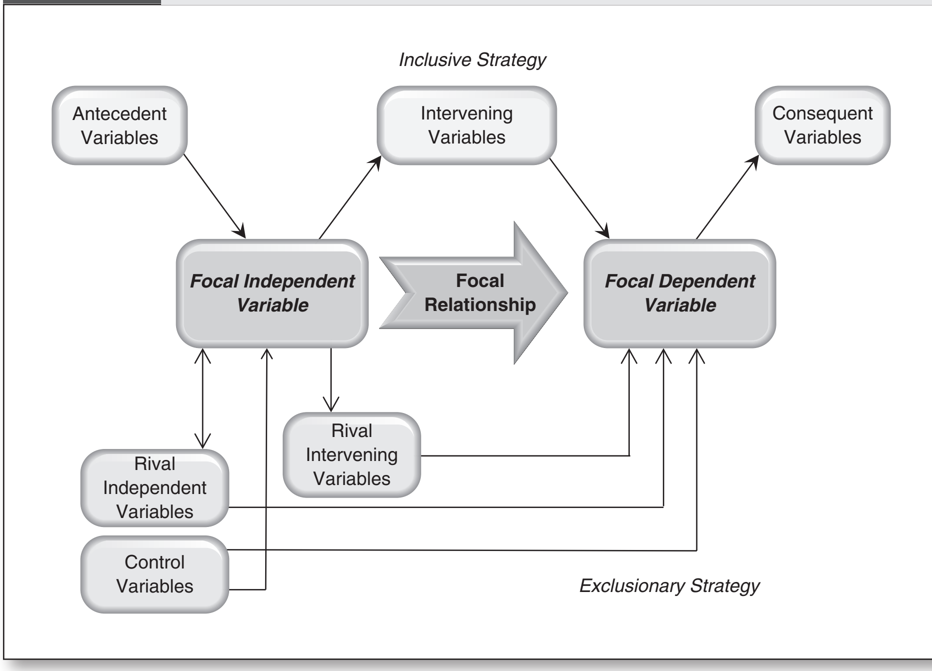
The first analytic step is to establish that the focal relationship is feasible—that two variables may be related to one another. This goal is realized by demonstrating that the two variables are empirically associated with one another in the manner predicted by theory and at a level beyond that expected by chance. After establishing association, further analysis serves to evaluate whether the focal relationship is a relationship or just an association.

The idea of a focal relationship is a natural extension of the elaboration model. Indeed, its presence is implicit in the original model insofar as third variables are used to enhance the interpretation of one basic association. Labeling this association as the focal relationship serves to move one independent and one dependent variable to the forefront of the analysis and to maintain this center of attention as other variables are added to the model. This device becomes more serviceable as the number of variables in the analysis increases.

Complementary Analytic Strategies

The two analytic strategies used to establish the focal relationship as a cause-and-effect type of relationship are illustrated in Figure 1.1. The first is an **exclusionary strategy**: ruling out alternative explanations for the association to substantiate the focal relationship as a

Figure 1.1 The Elaboration Model of Theory-Based Data Analysis



Note: The elaboration model employs two strategies to assess whether the association between a focal independent variable and a focal dependent variable can be interpreted as a causal relationship. The *exclusionary strategy* rules out alternative explanations such as spuriousness (control variables) and redundancy with competing theories (rival independent and intervening variables). The *inclusive strategy* connects the focal relationship to a surrounding network of other relationships that specify the origins of the focal independent variable (antecedent variables), the sequelae of the focal dependent variable (consequent variables), and the causal mechanisms that link the focal independent and dependent variables (intervening variables).

relationship. The goal is to ascertain the extent to which the association is the result of influences other than the hypothesized relationship and to exclude these influences from the estimate of the focal relationship.

The exclusionary strategy involves the analysis of **control variables** to eliminate **spuriousness**, which is the mistaken appearance of a relationship between two variables that have no causal relationship to one another, an association that is created by their joint dependence on a third variable; that is, they share a common cause. The exclusionary strategy also entails the introduction of **rival independent variables** to take into consideration **redundancy**, which is relatedness that the **focal independent variable** shares with other independent variables that represent competing theories. These rival independent variables are included in the analysis to identify any nonspurious influence on the **focal dependent variable** that is unique to the focal independent variable by a process of elimination. This strategy is exclusionary in the sense that it concerns the association remaining when these other processes have been removed from the estimate of the focal relationship.

Control and rival independent variables may account for some or all of the association between the focal independent and dependent variables. That is, the apparent focal relationship may in fact be spurious or the result of causal processes that are part of another theory. This outcome is satisfactory if some of the empirical association between the focal variables remains, but it disconfirms the theory under consideration when these third variables fully account for the empirical association. In other words, the inference of causality is supported when other explanations do not account for all of the association.

As illustrated in the upper panel of Figure 1.1, the second approach is an **inclusive strategy** that seeks to strengthen causal inference by ascertaining the extent to which the focal independent variable and the focal dependent variable are associated with other variables as specified by the theory being tested. This approach is useful when we think that the focal relationship is embedded within a network of relationships with other constructs. These other constructs include **antecedent variables**, which are determinants of the focal independent variable and extend the causal process back in time; **intervening variables**, which describe the particular ways in which the focal independent variable influences the dependent variable that are specified in the theory under consideration; and **consequent variables**, which are outcomes of the focal dependent variable and extend the causal process forward in time.

Of these variables, the intervening variable is the most important because it represents the causal mechanism that supposedly produces the focal relationship. Specifically, intervening variables are thought to be affected by the focal independent variable and, in turn, to affect the focal dependent variable, thereby transmitting the effect of the focal independent variable to the focal dependent variable. Intervening variables are also known as **mediators**, and their analytic role is referred to as **mediation**.

A third exclusionary strategy also entails causal mechanisms—those that are components of competing theories. These mechanisms are operationalized with what I refer to as **rival intervening variables** because they represent alternative accounts of how the focal independent variable influences the focal dependent variable. In this instance, the issue is not whether the focal relationship is a relationship, but whether it is generated in the manner posited by the theory applied in the study or by other processes. When these variables are included in the model, the term **focal intervening variable** is used here to distinguish the causal mechanisms of the theory being tested.

Antecedent, intervening, and consequent variables explicate the functioning of the causal system of which the focal relationship is a part. When expected patterns of association with the focal independent and dependent variables do indeed materialize, the inference of causality is supported. This is an inclusive approach in that it brings other explanatory variables into the analysis of the focal relationship.

The analytic strategies described thus far have assumed implicitly that the focal relationship applies to everyone and under all circumstances, but the theory being tested may specify a **conditional relationship**, such that the effect of the focal independent variable on the focal dependent variable is not fixed across the values of the third variable; on the contrary, this effect varies as a function of these values. This particular type of third variable is called an

effect modifier, **moderator**, or **moderating variable**—synonyms signifying that the focal relationship differs in magnitude, shape, and/or sign across its values. Conditional relationships are included under the inclusive strategy because they take the focal relationship as given and bring a third variable into the analysis to more precisely identify for whom or under what types of circumstances it applies.

An example can be found in the relationship between perceived age discrimination and psychological distress. Perceived age discrimination follows a U-shaped distribution with age: It is high during the 20s, drops in the 30s, and then increases and peaks between ages 50 and 60, followed by a sharp decline (Gee, Pavalko, & Long, 2007). More to the point, the association between perceived age discrimination and greater psychological distress is stronger for women than for men (Yuan, 2007). In other words, as perceptions of age discrimination increase, symptoms of psychological distress increase, and they increase at a greater rate among women than among men.

The exclusionary strategy is implemented before the inclusive strategy. This order makes sense because there is no reason to elaborate the focal relationship with the inclusive strategy if all of the association between the focal independent and dependent variables can be attributed to chance, spuriousness, or redundancy with other causal factors.[10]

Interpretation of Findings

Ideally, we have found that (a) the focal independent variable is associated with the focal dependent variable in the manner described by theory and at a level beyond chance; (b) some of the association remains intact when the alternative explanations of spuriousness and redundancy are taken into account; (c) the focal relationship fits within an interconnected set of relationships predicted by theory, especially the causal mechanisms linking the focal independent variable to the focal dependent variable; and (d) any conditional effects specified by theory exist. Given these favorable findings, we conclude that the theory is supported by the data.

All this having been said, this conclusion nevertheless remains provisional. Future research eventually may disconfirm one's findings. This possibility cannot be eliminated because any one test of the theory is based on a particular case and another particular case may contradict it—and there are an infinite number of particular cases. Also, there are likely to be multiple theories that are consistent with the data, making this standard insufficient to validate the theory. Science is an open-ended inquiry, where conclusions more often than not are modified by subsequent research. This is a desirable quality of research because it contributes to the accumulation of knowledge about the phenomenon under investigation. In addition, the theory has been tested with estimates based on the sample data that are then generalized to the population using inferential statistics; this methodology leaves open the possibility that the findings have been obtained by chance because samples are subject to random fluctuations.

If instead, there is no association between the focal variables at the start of the analysis, or if there is an association but it is completely spurious or redundant, then the model is discredited: There is no association that would support the inference of relatedness. Before rejecting the theory outright, however, the possibility that these negative findings are due instead to chance or to some flaw in the research design should be considered. For example, slippage between the measured variable and the construct it manifests—poor reliability or validity—introduces error that may obscure the existence of a true relationship. The correspondence between a sample and the population it represents may be poor and sampling fluctuations introduce the possibility that these are chance findings. It follows then that the theory may indeed be correct despite the one negative test of it. Evaluating this possibility usually necessitates testing the theory again with different data.

The elaboration model is an inferential model. It does not directly demonstrate cause and effect; rather, it establishes that such effects are probable by systematically eliminating alternative explanations while conforming to theoretical expectations. Ideally, all possible alternative reasons for the association between the focal independent and dependent variables would be identified, tested, and ruled out, and the researcher left with one and only one explanation—the hypothesized relationship. However, the universe of potential explanations is infinite and cannot be exhaustively tested. In practice, then, one seeks to narrow down a broad range of alternatives to a small number of plausible ones and take them into consideration in the design of the study or, more commonly, during data analysis. And, as just mentioned, the use of sample data means that the results, positive or negative, may be chance findings. For these reasons, the inference that an association is a relationship necessarily remains somewhat speculative. Finally, the model is probabilistic rather than deterministic. It does not identify the necessary and sufficient causes of an outcome but elucidates the factors that make that outcome probable.

The Elaboration Model Illustrated: Boundary-Spanning Work Demands

The analytic strategies just described are illustrated here with a recent study by Glavin, Schieman, and Reid (2011) on an emergent source of stress and its emotional impact—boundary-spanning work demands, which are demands that arise in the work domain but influence the performance of family roles. Figure 1.2 presents the study's theoretical framework modified to emphasize one focal relationship that is tested with an exclusionary strategy and elaborated with an inclusive strategy.[11] In this adaptation of the original research, the focal independent variable is work contact outside normal working hours and the focal dependent variable is guilt. The focal relationship hypothesizes that feelings of guilt increase as work contact increases.

Turning first to the focal independent variable, Glavin and colleagues (2011) maintain that boundary-spanning work demands are experienced as stressful because they are incongruent with the nonwork context in which the person is immersed, leading

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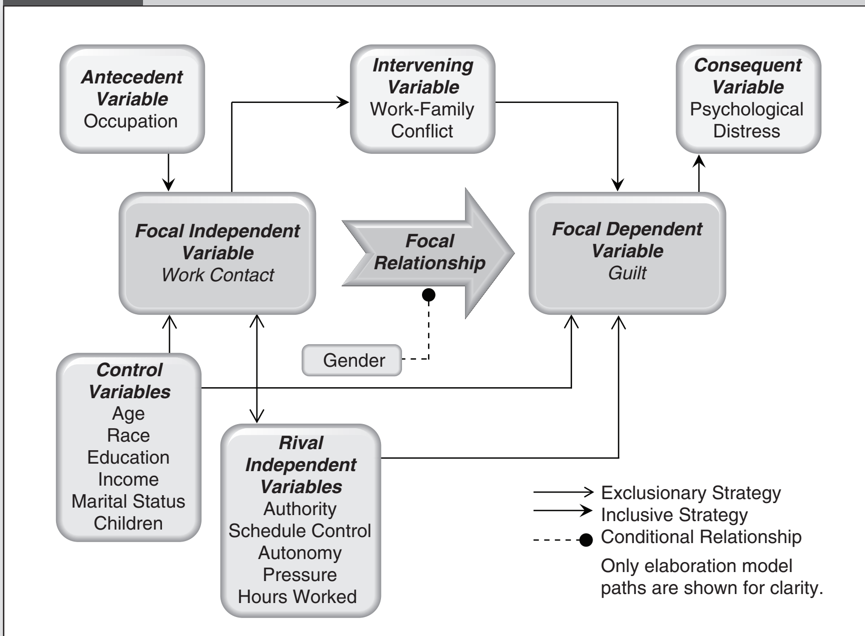
Figure 1.2 The Elaboration Model: Boundary-Spanning Work Demands and Guilt



Source: Adapted from Glavin et al. (2011).

Note: For this example, the focal relationship is the impact of work contact outside working hours (e.g., e-mail) on feelings of guilt. The *exclusionary strategy* is implemented with control variables, such as age, to rule out spuriousness; and rival independent variables in the form of occupational characteristics to exclude competing theories. The *inclusive strategy* encompasses the antecedent variable of occupation; the intervening variable of work–family conflict to explain how work contact produces guilt; the consequent variable of psychological distress to assess the impact of guilt; and gender as a moderator of the influence of work contact on guilt.

to "role-blurring." They distinguish role-blurring from the more frequently studied work–family conflict, which refers to mutually *incompatible* work and family demands (e.g., being in a work meeting vs. at the pediatrician's office) as distinct from *simultaneous* or overlapping demands (e.g., responding to work e-mails at the pediatrician's office) in these two domains. The investigators attribute scholarly interest in role-blurring to changes in how work and family are now structured, including the increase in nonstandard and flexible work schedules, as well as the proliferation of communications technologies, like the smartphone and e-mail. The particular type of boundary-spanning work demands examined in this study is receiving work-related contacts outside normal work hours, making work contact the focal independent variable.

As shown in Figure 1.2, the focal dependent variable is guilt, which refers to unpleasant thoughts or feelings that accompany the perception, accurate or imagined, that one has committed a breach of moral or social standards—has done something "wrong." Glavin and associates (2011) summarize research suggesting that being unable to meet family-related demands and expectations evokes feelings of guilt. They then reason that workers who deal with work at home, whether voluntarily or out of necessity, will experience more guilt than those who do not, which is the focal relationship.

The exclusionary strategy takes two forms in this example, as shown in the lower panel of Figure 1.2. The first is ruling out spuriousness. The set of control variables used to accomplish this objective are age, race/ethnicity, education, income, marital status, and number of children in the household. The second exclusionary strategy entails redundancy.[12] For the purpose of this example, the rival independent variables that signify competing theories are other aspects of the work environment that may affect emotions—authority, control over one's work schedule, autonomy, job pressure, and hours worked. Although these work conditions may be associated with the frequency of work contacts outside work hours, work contact does not necessarily depend on these conditions in a causal manner (as indicated by the bidirectional arrow in Figure 1.2); for this reason, these work conditions can be thought of as rival independent variables rather than as controls for spuriousness.

Several aspects of the inclusive strategy also are in evidence in this study, as can be seen in the upper panel of Figure 1.2. First, one's occupation (e.g., professional, administrative, craft, or labor) can be seen as an antecedent variable influencing the occurrence of work contact, the focal independent variable. Second, Glavin and colleagues (2011) hypothesize that work contact outside working hours leads to the experience of work–family conflict, which then arouses feelings of guilt, thereby explaining *how* work contact generates guilt. Thus, work–family conflict functions as an intervening variable, operationalizing the causal mechanism that is thought to produce the focal relationship. Third, psychological distress acts as a consequent variable, a condition that results from feelings of guilt.

The fourth element of this inclusive approach asks whether the focal relationship applies to everyone equally or is conditional on gender. While acknowledging substantial changes in men's and women's family and work roles, Glavin and his collaborators (2011) enumerate several reasons why the encroachment of work into the family domain may be more problematic for women than for men. For instance, they contend that the traditional masculine stereotype of breadwinner, a standard that is still applied to men often, makes it "natural" for men to combine work and family, whereas women are likely to perceive that work has prevented them from performing their family and household roles adequately. Thus, the investigators hypothesize that work contacts outside working hours are more strongly related to guilt among women than among men.

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The data for this study are from the 2005 Work, Stress, and Health Survey (WSH), a telephone survey of a national sample of adult (18 years and older) labor force participants (analytic n = 1,042). *Work contact* was assessed by asking, "How often do coworkers, supervisors, managers, customers, or clients contact you about work-related matters outside normal work hours? Include telephone, cell phone, beeper and pager calls, as well as faxes and e-mail that you have to respond to." Response codes ranged from 1 for "never" to 5 for "one or more times a day." *Guilt* was measured by asking, "In the past seven days, on how many days have you felt guilty?" The method of analysis is an **ordinary least squares regression** (OLS) analysis conducted in a series of steps that approximate the elaboration model presented here.[13]

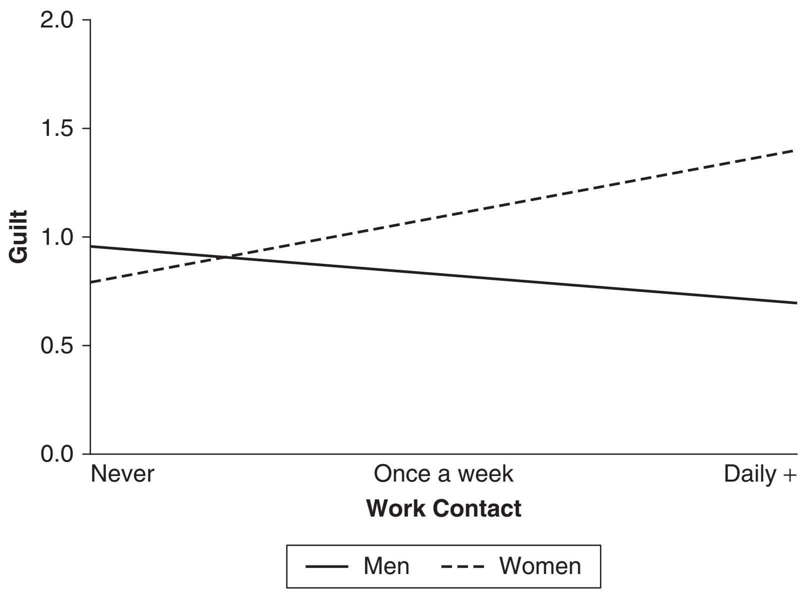
Contravening the idea that boundary-spanning work demands engender guilt, this emotion is not associated with the frequency of work contact for the sample as a whole. Notably, guilt does not differ by gender, other factors held constant.

Guilt is associated with two of the rival independent variables: Persons in jobs with a lot of authority feel guilty less often than those who have little influence, and an inordinate amount of job pressure coincides with frequently feeling guilty. These feelings do not vary across types of occupations, the antecedent variable. The focal intervening variable of work–family conflict is associated with guilt in the expected direction, but it does not act as a mediator because the focal independent variable is not associated with the focal dependent variable, a condition for mediation to occur. The other variables in this model do not perform their assigned role in the analysis plan for the same reason. Collectively, this set of findings does not substantiate the underlying theory in any meaningful way.

Granting all this, the theory does receive substantial empirical support in the next step of the analysis when the variable representing the differential effect of work contact by gender is added. Figure 1.3 shows this conditional relationship as the difference in the slopes of the lines for women and men. Women experience more guilt when they receive frequent work contacts outside working hours than when these demands are infrequent. Among men, in stark contrast, levels of guilt remain essentially the same irrespective of how frequently they are contacted by coworkers, supervisors, managers, customers, or clients during these times. In other words, the focal relationship is found only among women.[14] The overall estimate of the focal relationship earlier in the analysis is the average effect for the sample as a whole. The absence of an association among men weakens the average effect, thereby obscuring the association between these variables among women.

This conditional relationship also shows that gender differences in feeling guilty are minimal when work contacts are infrequent, but when these demands occur several times a week or more, women feel guilty more frequently than do men. The contingent nature of gender differences in guilt is shown by the unequal distance between the lines as work-contact increases in Figure 1.3.

Figure 1.3 The Conditional Focal Relationship: Gender Differences in the Association Between Work Contact and Guilt



Source: Glavin et al. (2011). Reprinted with permission.

Note: This study finds that gender moderates the impact of work contact on feeling guilty. Among women, guilt significantly increases as work contact outside working hours becomes more frequent, but guilt is not significantly associated with work contact among men.

Because this contingency matches the predicted one, the idea that boundary-spanning work demands lead to guilt is supported. In addition, the focal relationship among women is not explained by spuriousness or redundancy because the effects of control and rival independent variables already have been taken into consideration. Nevertheless, the hypothesized causal mechanism does not account for the focal relationship among women because this relationship persists irrespective of the amount of work–family conflict women experience.

The analysis of the consequent variable of psychological distress also provides considerable support for the theory guiding this research. As is the case for guilt, the effect of work contact on psychological distress is conditional on gender: These contacts are not associated with psychological distress among men, but the more frequently women are contacted about work outside working hours, the greater their

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level of psychological distress. This effect is not due to work–family conflict. Quite the contrary, the greater psychological distress that women experience in response to boundary-spanning work demands is completely explained by taking into consideration the high levels of guilt that result from work contact among women but not men. In other words, feelings of guilt mediate the distressing effect of frequent work contacts outside working hours among women, so much so that it also accounts for the overall higher level of psychological distress among women workers compared with men workers.

Glavin and colleagues' (2011) overall conclusion is that boundary-spanning work demands are associated with emotional well-being, but only among women; men do not appear to be emotionally distressed by these demands. This finding does not imply that men are immune to the potentially adverse effects of boundary-spanning work demands, only that men do not appear to experience guilt or psychological distress as a result of these demands. They may find these intrusions stressful, but express their reactions in other ways, for example, by experiencing anger.

As the investigators emphasize, the impact of work contacts on women is not explained by work–family role conflict—the focus of most existing research pertaining to gender differences and to women. It follows that further theoretical development is warranted to delineate the pathways through which role-blurring leads to negative emotional consequences among women. Glavin and associates (2011) attribute their findings partly to the greater saliency of family roles for women than for men and note that the stronger emotional effects of boundary-spanning work demands on women is especially consequential given women's increasing participation in the workforce, which now approaches that of men.

Theory, Statistics, and Data Analysis

Theory and statistics constitute distinct components of social inquiry, and by custom are taught separately, but nonetheless are used optimally when linked to one another in theory-based data analysis. Theory by itself is a collection of ideas. Statistical procedures by themselves are no different from hammers, saws, and nails; shovels, rakes, and hoes; and pots, pans, and knives. These objects become meaningful only when used purposefully—in construction, for gardening, and for preparing dinner, respectively. In the social sciences, the optimal use of statistics is to put theory to the test by using a strategic data analytic plan, such as the one provided by the elaboration model. Kenny (1979) makes this point emphatically about causal inference:

> The term *correlational inference* should not be taken to mean that various statistics are by themselves inferential. Regression coefficients, factor loadings, and cross-lagged correlations do not, in and of themselves, have an inferential quality. Given a plausible

model, a statistic can be used for inferential purposes, but the statistic itself is merely a passive tool. Inference goes on in the head of the researchers, not in the bowels of the computer. (p. 2)

In contemporary social science research, data analysis most often entails the application of multivariate statistical procedures to quantitative data. This tendency has emerged because research has relied increasingly on quantitative rather than on qualitative data and because multivariate statistics constitutes the most productive approach to quantitative data.[15] Empirical research, including the most circumscribed and straightforward of inquiries, generates an enormous mound of information. The sheer volume of information makes it unlikely that it can be grasped solely by exercising one's intellect. When the number of observations is large, keeping track of even one piece of information—such as responses to a survey question asking whether one voted in the last election—can be challenging. Data analysis, therefore, requires statistical techniques if for no other reason than to reduce the volume of information and to present it in a comprehensible summary form.

The analytic task becomes increasingly complex when two or more variables are considered simultaneously. For example, a survey of voting behavior probably also would examine the extent to which casting a ballot in the last election varies according to characteristics such as age, gender, race/ethnicity, political party membership, religious beliefs, social networks, and so on. Detecting such associations requires the simultaneous manipulation of numerous pieces of information, a task that is made possible through the application of various statistical procedures for multivariate analysis.

The ascendancy of multivariate quantitative statistical methods also derives from its close alignment with the complexity of social science theories that specify multiple influences on outcomes and contingencies among these influences. Early theory-driven quantitative research in the social sciences generally employed a constricted set of variables because statistical calculations were done with calculators prior to the advent of the information-computer revolution. An analysis of covariance was an accomplishment in itself. Thus, researchers were unable to simultaneously examine the full spectrum of potential influences on the phenomenon under investigation.

Multivariate statistical techniques became the norm with the arrival of mainframe computers with multipurpose statistical software packages that contained user-friendly syntax, although the capacity of early versions of these packages was limited, for example, having restrictions on the number of variables that could be analyzed at one time. Advanced multivariate statistical techniques that are commonplace now were beyond the capability of the most powerful mainframes not all that long ago. The availability of large data sets, including public use national longitudinal surveys, also has accelerated the movement toward research employing these techniques because their large samples enable complex statistical models. The current state of fingertip access to software that accommodates large numbers of variables and big sample sizes, therefore, has fostered multivariate statistical analyses that can provide more rigorous tests of multifactorial theories.

At times, however, evolving statistical techniques and software technology seem to drive research, perhaps because it is seen as cutting edge and, therefore, somehow better than methods that already have been widely applied. Thus, the most recent statistical techniques may be used because they are novel or trendy, and not necessarily because they are best suited to the research question. The formidable mathematical foundation for many of these methods makes them difficult to understand for many researchers, thereby adding luster to their image of superiority. To illustrate this point, the development of software to conduct multilevel models about a decade ago has supported a multimillion-dollar cottage industry of research on neighborhood effects on health.

As a consequence, theoretical considerations may be given insufficient attention because the statistical models are so complex, technical, and powerful that implementing them correctly may overwhelm other considerations. The analysis sections of research reports, for example, commonly identify the statistical techniques used to analyze data in lengthy detail replete with complex equations without necessarily mentioning how these techniques correspond to the conceptual orientations motivating the research.

The tendency to privilege complex statistical models is facilitated by user-friendly statistical software packages that make it possible even for novices to compute complex mathematical models almost instantaneously, which may lead to being caught up in the analysis itself and to losing sight of its purpose. It is not necessary to give much thought to the specification of an analytic model when it is a simple matter to change it in a subsequent run and receive immediate results. This type of modification of a model, however, easily becomes an empirical matter rather than a theoretical one. The model is refined based on technical feedback as distinct from the conceptual specification of the relationship being tested and its alternatives, for example, adding a term to a model based on the extent to which it will improve a fit index. The empirical modification of statistical models may inadvertently move the analysis further away from the theoretical model, subverting the purpose of the analysis. Although empirical modifications are appropriate in many instances, they do not originate in the theoretical specification of relationships among constructs and, hence, may only incidentally advance the interplay between theory and observation.

The detachment of theory from the statistical manipulation of data also flows at least in part from a disproportionate emphasis on maximizing the explained variation in the dependent variable, as if that were the sole purpose of the analysis. This is an orientation that prevails in many statistics courses and in numerous textbooks. This perspective tends to equate the importance of an independent variable with the empirical magnitude of its contribution to explaining the dependent variable, whereas its importance also is derived from its role as a test of theory. It is easy to become distracted by independent variables that add considerably to the explanation of the dependent variable, including variables that have little or nothing to do with the theory being studied. This approach has it merits, but testing theory is not necessarily one of them.

This approach is suitable, for instance, with atheoretical multivariate analysis, when the goal is a descriptive summary of the associations between numerous covariates and a dependent variable that does not attribute causal influence to those covariates. For example, in public health research, a risk factor is differentiated from a risk marker in that the former is part of a causal chain that results in an increased chance of having a health condition, such as being sedentary and having coronary heart disease, but the latter is associated with the health condition without necessarily causing it; it identifies populations that should be monitored. A recent study of domestic violence in Peru, for instance, used multivariate analysis for this purpose and found that living in a non-coastal area and having an urban residence increases the likelihood of being the victim of intimate partner violence (Flake, 2005). In other applications, multivariate analysis is used to predict an outcome as distinct from explaining it, such as the use of personality tests to predict job performance; maximizing explained variance increases the accuracy of the prediction.

One application of atheoretical multivariate analysis, however, is of dubious merit: The search for a research question by probing the data for interesting patterns of association that are then crafted into a theoretical framework that purportedly forms the basis for the data analysis. Deriving a theory on the basis of such an analysis may be legitimate, but testing that theory with the same data is inherently problematic because it is circular and deceptive. The formulation of scientific hypotheses flows from theory to the application of the correct statistical techniques to suitable data and not from the application of a particular statistical technique to available data in search of a hypothesis and a theory (Kenny, 1979).

The difficulty for theoretical research lies not with the application of multivariate statistics per se. Rather, the problem arises from the inadequate synthesis of theory with statistical technique. That is, theory does not sufficiently inform the selection of statistical procedures, and the results of quantitative analysis are only tangentially relevant to conceptual models. Although research questions should inform the selection of statistical techniques, the reverse seems to be a common occurrence. For example, logistic regression may be selected solely because the outcome is a **dichotomous variable**; that is, it has only two values, such as a disease being "present" versus "absent," with little attention given to the selection of demographic control variables to include in the regression, relying on the "usual suspects" without reasoning through the connection of each variable to the focal independent and dependent variables and to each other. The consequence all too often is disembodied results—results whose connection to the underlying theory is at best oblique.

Thus, the statistical manipulation of numbers is sometimes separated from the logical manipulation of ideas. This separation, in turn, impedes the cross-fertilization of theory and observation that is the catalyst for scientific discovery and explanation. On one hand, theoretical principles are not tested as directly or as efficiently as they might be and, hence, are not fully refined or developed. On the other hand, powerful statistical techniques often address issues other than the core theoretical principles and, therefore, generate insight into the data, but insight that is somewhat off target. Under these conditions, research necessarily fails to accrue its full potential.

The issue here is not error in the application of various statistical procedures, faulty technique. Rather, the problem lies with the selection of procedures that do not precisely operationalize the study's research questions and hypotheses. In other words, the statistics chosen do not test theory-based hypotheses. To be sure, the statistical procedure tests some hypothesis but not necessarily the most relevant one. In this regard, Kenny (1979) concludes that failure to apply the appropriate statistical method given the conceptual model produces many of the more serious errors in data analysis, not lack of knowledge of statistical methods; he points out that Levin and Marascuilo (1972) have called this mismatch Type IV errors.

All that having been said, sophisticated and innovative statistical techniques in contemporary quantitative social science research are advantageous when the technique provides the best method of analysis for attaining the objectives of the research. This consideration implies that the research question and the method should be aligned as closely as possible. In the instance of theory-based data analysis, this criterion means that theory should inform the selection of a statistical technique rather than the other way around. When this is the case, advanced statistical techniques often can be used to overcome limitations of previous research and make the maximum use of the data, although in other instances, more conventional methods of analysis may better serve the objectives of the research. In any event, the translation of theory into a logical data analytic plan entails the same type of reasoning across many statistical techniques.

The elaboration model of theory-based analysis presented in this text seeks to correct the course that quantitative data analysis has taken in recent years. It does so by emphasizing a single focal relationship so that the goal of the analysis remains in focus throughout the analysis. It then presents a strategic analytic plan for ascertaining the extent to which it is plausible to infer that the empirical association between the focal independent and dependent variables represents a cause-and-effect type of relationship. The overarching goal is to align the data analysis with the theory guiding the research.

The Inherent Subjectivity of Analysis

It is important to acknowledge at the outset that data analysis is never entirely objective. What one sees in a set of data is inevitably shaped by what one expects to see. The notion that data analysis is subjective runs counter to the traditional principles of science, which dictate that research is conducted in an impartial manner. The image of the researcher as a neutral observer and reporter, however, is an ideal that is not capable of being fully actualized.

The inherent subjectivity of data analysis becomes self-evident when we recall that analysis is conducted within the context of theory, which is itself a statement of what one expects to find. Theory shapes the very questions that are asked, the data selected to answer these questions, and the methods applied to these data. The interpretation of analytic results, therefore, is affected by one's theoretical inclinations. Keller (1985) cogently articulates this viewpoint:

> Let the data speak for themselves, these scientists demand. The problem with this argument is, of course, that data never do speak for themselves. It is by now a near truism that there is no such thing as raw data; all data presuppose interpretation. And if an interpretation is to be meaningful—if the data are to be "intelligible" to more than one person—there must be participation in a community of common practices, shared conceptions of the meaning of terms and their relation to "objects" in the real world . . . it means sharing a more or less agreed-upon understanding of what constitutes legitimate questions and meaningful answers. Every explicit question carries with it a set of implicit (unarticulated, and often unrecognized) expectations that limit the range of acceptable answers in ways that only a properly trained respondent will recognize. Thus for every question such as "What accounts for X?" the range of acceptable answers is circumscribed by unspoken presuppositions about what counts as accounting—a circumscription that is assumed as a matter of course by members of a particular community. (pp. 121–130)

These comments do not imply that the researcher has license to indulge his or her personal predilections. On the contrary, acknowledging the pervasive influence of presupposition is a warning: One should be alert to tacit assumptions that limit analysis and constrict interpretation.

It is especially easy to lose sight of the impact of expectations when pouring over quantitative results produced by the application of sophisticated statistical procedures. Computer output crammed full of numbers and statistics creates an illusion of factual reality. The application of formal tests of statistical significance further embellishes this image. Despite the illusion of impartiality created by quantitative analysis, it must be recognized that tacit theoretical assumptions affect the selection of statistical procedures, the choice of variables entered into an analysis, and so forth. Although quantitative analysis may mask this type of subjectivity, it does not produce findings that are objective in the absolute.

The analyst is like an artist. He or she observes a mass of information that dazzles with multifaceted possibilities. These impressions spark the imagination. The analyst-artist selects and arranges these images to communicate his or her vision to others. Some elements are pulled to the forefront and depicted in minute detail, whereas others form the middle ground or fade into the vagueness of the background. This ordering of impressions is an act of creation: The vision being communicated is that of the analyst-artist. The same objects would appear differently if viewed from another vantage point: An element relegated to the background might well become the focal point. One researcher's independent variable, therefore, may well be another's dependent variable. Alternately, shifting perspectives may reveal an object previously concealed from view. Representations of the same scene created by different artists often bear little resemblance to one another.[16] The act of observing and communicating is no less subjective because the analyst works with numbers, computers, and statistical output rather than visual perceptions, easel, and canvas.

This perspective is similar to Bacon's view of the ideal analogy for science (cited in Lloyd, 1996):

> Neither the activity of the ants, who merely heap up and use their store, nor that of the spiders, spinning out their webs; but rather that of the bee, who extracts matter from the flowers of the garden and the field, but who works and fashions it by its own efforts. (p. 50)

The strategies presented in this text are tools for transforming a set of empirical associations into a coherent test of theoretical causal processes. This method is capable of demonstrating that the observed data are consistent with theory, but it falls short of demonstrating that the theory is factually true because there always remain alternative accounts for the same pattern of association. This caveat serves as a reminder that we should not confuse our representations of reality with reality.

Summary

The chief function of data analysis as envisioned in this text is to connect the theoretical realm with the empirical world. Theory describes an imaginary world. The presence of this world is inferred from observations made from the empirical or "real" world. This empirical world consists of direct experience—that which can be touched, tasted, seen, heard, or smelled. It is material, factual, and perceptible. It can be experienced firsthand.[17]

The attribution of meaning to these immediate sensations, however, is a theoretical construction. First, theory selects, sorts, and classifies direct observations. The essence of these observations is abstracted and conceptually interpreted. These interpretations result in the description of hypothetical constructs and how these constructs are connected to one another.

Data analysis presupposes that the theoretical and empirical realms are aligned with one another. Abstract notions about how constructs are related to one another are put to the test by estimating associations among measured variables within a sample. In this manner, constructs are operationalized as measured variables, relationships are estimated as empirical associations, and populations are represented as samples. Findings from the concrete analysis of associations among variables within a sample are used to make inferences about probable relationships among constructs within a population. These findings then contribute to the development of theory, which eventually leads to another test of it.

The elaboration model used in this text is an effective method for evaluating a theory with strategic data analysis. It starts with an empirical association between the focal independent and dependent variables that we would like to interpret as a relationship between the corresponding two constructs. Whether it constitutes a relationship is tested first with an exclusionary strategy, seeking to rule out alternative explanations to relatedness, such as spuriousness and redundancy. Second, an inclusive strategy is used to assess whether a causal inference is warranted. The focal independent and dependent variables are linked to a network of hypothesized relationships with other variables, including those that operationalize the putative causal mechanism. Then, conditional associations are examined to ascertain whether the focal relationship is universal or is limited to select groups or conditions as specified by theory. In combination, these analytic strategies enhance the inference of cause and effect in research that uses observational data.

This theory-based approach to the focal relationship represents an ideal analytic strategy, and in practice, many applications fall short of this ideal. For example, the theory being evaluated may not be developed sufficiently to specify fully the processes that generate the focal relationship, or measures of key third variables may be missing from the data set. Even in such circumstances, however, the elaboration model is apt to move the analysis in theoretically relevant directions.

There are other strategies for theory-based data analysis and even more techniques for data analysis in general. These approaches can supplement the approach described in this text or serve as productive alternatives. There is no one right way to analyze data. Just the opposite. The focal relationship and the elaboration model are presented as one of several methods of implementing theoretically coherent analysis.

Looking Ahead

This text presents the reasoning and statistical techniques used in applying the elaboration model of theory-based data analysis to the question of whether an empirical association estimated between two measured variables using sample data can be interpreted logically as a probable causal relationship between the analogous constructs in the corresponding population. It unfolds in the following manner.

Chapter 2 describes the major lines of reasoning that are used in theory-based data analysis, specifically the complementary forms of inductive and deductive reasoning with regard to the development and testing of theory, respectively. These ideas are then aligned with the reciprocal processes of operationalization and assessment of fit between theory and data for the following core elements of theory-based research: constructs as mirrored by measured variables, populations as reflected in samples, and relationships as mimicked by empirical associations. The chapter then explains why tests of theory seek to refute it more so than to show that it is supported by data. It concludes with a discussion of why scientific findings necessarily are provisional, a rather unsatisfying state for those who seek certainty.

Chapter 3 explains what it means to say that two variables are associated with one another in the manner *specified by theory* and that this association is accounted for by a third variable. This conceptual material provides a foundation for the statistical analyses that constitute most of the text. The chapter begins with the idea that an association occurs when two variables covary with one another and that this covariation may take various shapes and forms. It then addresses how the total association estimated with bivariate analysis becomes a partial association when a third variable is added to the analysis and when multiple third variables are added. The discussion emphasizes the consequences of changes in the magnitude of the association for the interpretation of the association that remains when these other variables are taken into consideration statistically, if any association remains. In particular, the interpretation that adheres to this residual association under the exclusionary strategy is contrasted with the opposite interpretation that pertains under the inclusive strategy. The chapter ends with the question of whether the focal relationship applies under all circumstances and for everyone, or whether it applies only under some circumstances or for some people.

The inference that an empirical association between the focal independent and dependent variables signifies a cause-and-effect type of relationship among the parallel constructs is addressed in Chapter 4. The chapter begins with a discussion of the general issue of causality and then reviews criteria for asserting a causal interpretation for an empirical association based on observational data. Several threats to internal validity are described along with approaches to resolving these threats. Then, the several steps of the exclusionary strategy are applied to this issue, with the goal of ruling out the possibility that the association between the focal independent and dependent variables is merely the result of chance or coincidence. Next, we turn our attention to perhaps the most powerful aspect of the analysis, ascertaining whether the hypothesized causal mechanisms appear to be operative. The chapter concludes by differentiating the primary focus of the analytic plan—explaining the focal relationship—from the aligned goal of most analyses—explaining the dependent variable.

Chapter 5 reviews basic aspects of multiple linear regression as they pertain to the implementation of the elaboration model of theory-based data analysis of data obtained from a simple random sample (SRS; see Note 5). However, much of the data analyzed by social scientists derive from surveys conducted with complex samples. Consequently, Chapter 6 describes complex samples and the application of multiple linear regression to data obtained from such samples (see Note 5).

Most of the remaining chapters proceed through the steps of applying the elaboration model using multiple linear regression. Chapters 7 and 8 concern the exclusionary strategy and deal with ruling out the effects of spuriousness and redundancy, respectively. Chapters 9, 10, and 11 address the inclusive strategy. Chapter 9 covers the important topic of assessing causal mechanisms using mediation analysis. The ways in which antecedent and consequent variables are used to strengthen causal inference are discussed in Chapter 10. The last part of the inclusive strategy, specifying the conditions under which the focal relationship functions and for whom, is addressed in Chapter 11.

The implementation of the elaboration model with logistic regression is taken up in Chapter 12 because the exclusionary and inclusive strategies are applied differently than in multiple linear regression. For reasons that are explained in Chapter 12, the statistical basis of the logistic model makes it incorrect to compare unstandardized logistic regression coefficients across models as variables are added, although this has been a common practice in existing research. The assessment of conditional relationships with interaction terms or with subgroup analysis also is affected by this issue. However, the logic of the elaboration model can be applied to the analysis of dichotomous variables with logistic regression, and the most important aspects of the empirical test of the theoretical model can be obtained as well. Nevertheless, the logistic model is sufficiently distinctive to warrant its treatment in a separate self-contained chapter that applies the elaboration model of theory-based data analysis.

Chapter 13 synthesizes this material and ties up loose ends. The question of causal inference is revisited as well in this chapter.

Throughout the text, the logic of the analytic strategy and the application of statistical technique are illustrated in two ways. First, I cite exemplars from recent research that illustrate the alignment of theory and statistics, presenting these case studies in some detail, as done in this chapter for the study of boundary-spanning work demands.

Second, I present two extended empirical examples with original data analysis.[18] One is a study of Los Angeles County residents about their experiences during and immediately after the 1994 Northridge earthquake, which caused substantial loss of life, injury, and property damage. The data for the Northridge Earthquake Study were collected from a community-based sample of Los Angeles County residents using a random-digit dial telephone survey (Bourque, Siegel, & Shoaf, 2002). The method of sampling approximates an SRS, and these data, therefore, are used to illustrate multiple linear regression and logistic regression using standard statistical procedures that assume an SRS.

The other example is based on survey data from the Health and Retirement Study (HRS), a biennial longitudinal, multicohort survey of a large, nationally representative sample of persons aged 50 and older begun in 1992, which contains information about work, family, finances, health, future plans, and sociodemographic characteristics (Health and Retirement Study, n.d.). Data from a 2006 and 2008 supplemental psychosocial questionnaire are analyzed here, focusing on constructs such as life satisfaction, loneliness, discrimination, and social support. These data are used to illustrate the analysis of survey data from complex samples, which has become an increasingly common staple of social science research.

Collectively, the case studies and empirical examples provide a comprehensive road map for how the elaboration model can be used to test social science theory.

Notes

1 Constructs and other terms are defined later in this chapter. Terms in bold appear in the glossary.
2 Unfortunately, the integration of analysis with other research components, such as sampling and instrumentation, is often overlooked when the study is being planned. For this reason, our tests of theory may be incomplete because crucial variables have not been assessed.
3 In experimental research, the independent variable is the one that is being manipulated by design and the dependent variable is the outcome that is expected to change as a result of the manipulation.
4 An example of social research where the sample unit is not people can be drawn from medical sociology. Suppose we are interested in how characteristics of medical care providers (such as age, gender, general practitioner vs. specialist) relate to the length of visits with patients. The units of observation would not be doctors or patients but visits because duration is a characteristic of the visit.
5 The **simple random sample** is a specific type of probability sample in which each unit of the population has an equal probability of selection. For probability samples in general, the probability of selection is known, but it does not have to be equal for all units of the population. In survey research, people (or aggregations of people, such as households) typically have unequal probabilities of selection. For example, it is common practice to oversample members of racial/ethnic minority groups to obtain sufficient sample sizes for analysis. In addition, survey samples usually employ **complex sample designs**, in which the population is stratified on some characteristics, and participants are selected from clusters within these strata. This type of sampling and its implications for analysis are discussed in Chapter 6.
6 In addition, evaluation research constitutes a distinct type of social research.
7 Quasi-experimental research, a hybrid type, often uses both strategies to establish internal validity: Threats to internal validity are controlled by design to the extent possible, and those that cannot be controlled by design are controlled through analysis.
8 Often this entails a causal relationship, but Rosenberg (1968) correctly notes that causality is only one form of determination.
9 The idea of the focal relationship is similar to Ernest Schachtel's idea of "focal attention," described by Keller (1985) as man's "capacity to center his attention on an object fully, so that he can perceive or understand it from many sides, as fully as possible" (p. 165). Jaccard (2001) also uses the term *focal* to refer to the independent variable whose effect on the dependent variable is moderated by a third variable using interaction analysis (see also Jaccard & Turrisi, 2003).
10 An exception to this order is rival intervening variables, which are commonly tested simultaneously with the focal intervening variables.
11 Although Glavin and associates (2011) use a similar method of analysis, they do not refer to the elaboration model, and they have several focal relationships, not one. Their model is recast here as one focal relationship for the purpose of illustrating the elaboration model.
12 This example illustrates only one form of redundancy—rival independent variables; rival intervening variables are not included in the analysis.

13 **Ordinary least squares regression** refers to a method of estimation for multiple linear **regression**, which is a statistical technique of estimating the effect of an independent variable on a dependent variable while controlling for the effects of other independent variables. Chapter 5 describes this method of analysis.

14 Although the slope for men appears to be slightly negative, it is not significantly different from 0, the value indicative of no relationship.

15 This statement is not intended to devalue qualitative research nor does it imply that the preponderance of quantitative research is desirable. It is a descriptive statement about the status quo. Whereas quantitative research often takes an explanatory form, it is not uncommon for qualitative research to focus on the subjective interpretation of the meaning of a particular phenomenon at a specific time and place. Also, theory-generating research tends to be qualitative, whereas theory-testing research tends to be quantitative. The recognition that these different vantage points can inform one another has led to the emergence of mixed methods research in the social sciences. In some instances, this approach merely involves appending a quantitative study to a qualitative one, or vice versa. However, the optimal mixed methods approach involves a synthesis of the distinctive ways in which the interpretive and explanatory perspectives view the phenomenon under investigation that frames the ways in which the research questions are formulated and informs the interpretation of study findings (Small, 2011).

16 A striking example of this aspect of artistic vision appeared at an exhibit Impressionists on the Seine: A Celebration of Renoir's "Luncheon of the Boating Party" shown at the Phillips Collection, Washington, D.C., September 21, 1996, to February 9, 1997. This exhibit presented side-by-side paintings of the same subject painted simultaneously by two impressionist masters—Claude Monet and Auguste Renoir. Particularly striking is the difference in palette and composition for the two pairs of identically titled paintings, Sailboats at Argenteuil and La Grenouillère (Rathbone, Rothkopf, Brettell, & Moffett, 1996; see also White, 1996, for other fine examples). Monet (cited in Levine, 1994) also gives us a powerful image for the impact of theory on observation when he notes, "One is not an artist if one does not carry a picture in one's head before executing it" (p. 270). See also Rosow (1994) for a discussion of Monet's method of visually capturing the changing effects of light and in particular how it serves as a model for social science research, both controlled experiments and, the topic of this text, the analysis of connections among multiple variables. In addition, Kemp (2000) provides an especially rich discussion of the shared motifs in the imaginary worlds of the scientist and the artist for whom the act of looking has the potential to become an act of analysis.

17 This empiricism derives from the philosophy of John Locke, who emphasizes the experiences of the senses in the pursuit of knowledge rather than deduction as in the Cartesian tradition.

18 These data are analyzed with Stata 12.1 (StataCorp., 2011). Chapter notes provide information about the implementation of statistical procedures with this software.