
ERIC J. KRIEG
2ND EDITION
STATISTICS AND DATA ANALYSIS FOR
SOCIAL SCIENCE

Variance (s^2)	A type of average. The average of the sum of squared distances from the mean.	$s^2 = \frac{\Sigma(X-\bar{X})^2}{N}$
Standard Deviation (s)	A type of average equal to the square root of the variance. It is the square root of the sum of squared "distances" from the mean.	$s = \sqrt{\frac{\Sigma(X-\bar{X})^2}{N}}$
Probability (P)	The likelihood of a particular event occurring.	$\frac{\textit{Number of outcomes in an event}}{\textit{Number of all possible events that can occur}}$
Z-Score or Standard Score (z)	The value of a particular case (x) relative to the mean (μ), measured in units of standard deviation (σ).	$z = \frac{x-\mu}{\sigma}$
Standard Error of the Mean For Populations: ($\sigma_{\bar{x}}$) For Samples: ($s_{\bar{x}}$)	A measure of variability in the sampling distribution of the mean.	For Population Data: $\sigma_{\bar{x}} = \frac{\sigma}{\sqrt{N}}$ For Sample Data: $s_{\bar{x}} = \frac{s}{\sqrt{N-1}}$
Dispersion in a Percentage	A measure of uniformity of responses.	$p(1-p)$
Standard Error of the Proportion (Sp)	A measure of variability in a sampling distribution.	$Sp = \sqrt{\frac{p(1-p)}{N}}$
Confidence Interval (CI)	A range of values in which the true population parameter is expected to fall.	$95\%\ CI\ for\ Proportion = P \pm (1.96)s_p$ $95\%\ CI\ for\ Mean = \bar{X} \pm (1.96)s_{\bar{x}}$
t-Ratio	A distribution that is used to determine probabilities when population parameters are unknown and estimated.	$t = \frac{\bar{X}-\mu}{s_{\bar{x}}}$
The Standard Error of the Difference Between Means ($S\bar{X}_1 - \bar{X}_2$)	A statistic that uses the standard deviations of two samples to estimate the difference between means.	$\sqrt{\left(\frac{N_1S_1^2+N_2S_2^2}{N_1+N_2-2}\right)\left(\frac{N_1+N_2}{N_1N_2}\right)}$
t test	A statistic used to determine the level of confidence at which the null hypothesis can be rejected.	$t = \frac{\bar{X}_1-\bar{X}_2}{S_{\bar{X}_1-\bar{X}_2}}$
Column %	Column Percent	$column\ \% = \frac{f}{N_{column}}(100)$
Row %	Row Percent	$row\ \% = \frac{f}{N_{row}}(100)$
χ^2	Chi-Square	$\chi^2 = \Sigma\frac{(f_o-f_e)^2}{f_e}$
df	Degrees of freedom for a frequency table.	$df = \#\,rows - 1$
df	Degrees of freedom for a cross-tabulation table.	$df = (\#rows-1)(\#columns-1)$
alpha	Level of Statistical Significance	

Statistics and Data Analysis

for Social Science

Second Edition

This book is dedicated to a better future for all people. Violence, inequality, and unsustainable consumption are a few of the unfortunate defining characteristics of our current world. The path to a healthier, less violent, and more egalitarian future is obscured by the inability to critically reflect on social structures that promote and perpetuate these problems. Statistical literacy is one of many tools that can be used to bring about greater clarity in thinking about a better tomorrow. That is the spirit in which this book was written.

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Preface

Over 25 years of teaching statistics, I have always been impressed with how well students calculate correct answers. Those who claim to be terrible at math usually have no problem in calculating a wide range of statistics, including measures of central tendency, dispersion, association, and confidence intervals. In a way, it simplifies much of their experience as social scientists. Because social science is often laden with theoretical interpretations of data, it is sometimes nice to just have an answer that is either right or wrong. The problem, however, is that getting a right or wrong answer is not an indicator of understanding why it is calculated or what it tells us about the world. Knowing how to mathematically calculate a one-way chi-square is different from knowing why anyone would bother to do it in the first place. Consequently, statistics is often learned in the context of "how to" rather the context of "for what purpose." No wonder students often don't know what the answers are telling them!

Like many instructors, I have struggled to find the right text. In the world of teaching and learning, problems often arise because of what is left out. As a group, statistics teachers are guilty of teaching a partial curriculum—one that emphasizes quantity and breadth over quality and depth. It is of no use to students to know how to calculate 30 different statistics if they don't know when to use them or what they mean. Too often, statistics books for undergraduates tend to present too many statistics in too complex a manner, thereby generating too much confusion. In response to this, I began formatting my class notes so that they would be suitable handouts for students. The notes eventually took the form of a short workbook intended to supplement a textbook. Over the years, teaching assistants made contributions to the workbook, and eventually it became more comprehensive. Students slowly began to use the workbook as a replacement for the texts that I assigned, and now it constitutes a text in and of itself. It is intended to overcome some of the problems that characterize introductory statistics courses by presenting statistics in a more user-friendly and applied way that connects statistical concepts and calculations to real-world examples.

This book reduces the number of statistical concepts presented to those that are most common, simplifies the complexity of statistical calculations to what is deemed most salient, organizes chapters around real-world applications or examples that act as references around which questions and discussions are organized, and provides a lot of practice problems at the end of each chapter with answers provided in the back of the book. These include Chapter Exercises and In-Class Exercises.

Many of the techniques and methods for computing statistics in other texts differ slightly from the techniques demonstrated here. I have tried to present the most understandable approaches, which is not to say that these are the only or best techniques, just that they are ones I have found to be most successful in my teaching. Major concepts are presented in as straightforward a manner as possible. The style of presentation comes primarily from students who first took the course and later assisted me with the course. The ideas presented here constitute the material most central to quantitative analysis in the social sciences and applicable to our everyday lives.

The order in which statistical concepts are presented is the order in which I teach them in my course; they have a logical sequence that allows students to build their statistical knowledge on top of what they learned in the previous chapters. I like to think of this as walking up a flight of stairs—getting to the top of the staircase in one huge step is impossible, but by taking it step by step it is easy (which is why I emphasize attendance so heavily in my course). You can think of each chapter as a step on our staircase. My hope is that this will expand students' imaginations in regard to the ways that these statistical "tools" can be used to make sense of our world and, maybe, to make the world a better place.

The book is not intended to be comprehensive. Statistical concepts that have less of a direct bearing on an undergraduate's investigation of the social world are not included. Nor will readers find chapters full of examples on how to analyze data using SPSS for Windows in this book. Instructors who wish to incorporate statistical software into their courses tend not to need a book that does so for them. This keeps the focus on how statistics are used. Chapter topics include inequality, education, income, toxic waste, sexism, status, and political ideology, among others. Wherever possible, examples are used so that students can get an idea of why a statistic, or a group of statistics, is used. In my experience, students who know when particular statistics might be applied tend to know how to calculate them. They also seem to have a clearer grasp of what those statistics tell us about the data. In some chapters, census data are used and discussions are included to make students aware of the differences between individual and ecological data.

A variety of pedagogical features are used to enhance each chapter:

Chapter Opening Examples. Each chapter opens with an example from the world around us to highlight the chapter material and show the role of statistics in everyday life.

Formula Tables. A summary table of key formulas and symbols used in the chapter is provided near the beginning of each chapter.

Now You Try It. After a statistical concept is introduced, students are given a few practice exercises to reinforce understanding. Answers to these exercises are provided at the end of the chapter.

Statistical Uses and Misuses. These boxes encourage students to be informed consumers of statistical information by giving real-world examples of how statistics can inform or deceive.

Eye on the Applied. These boxes take an important concept from the chapter and provide a case study example of how statistics reveal that the world is not always as it appears.

Integrating Technology. Optional technology examples describe the manner in which different types of technology facilitate the generation and interpretation of statistics.

In addition, definitions of key terms are included in the chapters, and the key terms are listed with page numbers of their definitions at the end of each chapter. Chapter Exercises, In-Class Exercises, and Homework Assignments are included for the benefit of students and instructors. These are found at the end of each chapter so that students can practice calculating and interpreting the statistics themselves.

These also give instructors a significant amount of material that they can use in class without needing to prepare handouts.

Additional digital resources further support and enhance the learning goals of this book. A password-protected instructor teaching site, available at **edge.sagepub.com/krieg2e**, provides integrated sources for all instructor materials, including the following key components for each chapter:

- The **Test Bank**, available in Word and ExamView, contains multiple-choice, multiple response, true/false, short-answer, and essay questions for each chapter. The test bank provides you with a diverse range of prewritten options as well as the opportunity to edit any question and/or insert your own personalized questions to assess students' progress and understanding effectively.
- Editable, chapter-specific Microsoft **PowerPoint® slides** offer you complete flexibility in easily creating a multimedia presentation for your course. Highlight essential content, features, and artwork from the book.

The open-access student study site (**edge.sagepub.com/krieg2e**) provides a variety of additional resources to build on students' understanding of the book content and extend their learning beyond the classroom. The website includes the following:

- **eFlashcards**: These study tools reinforce students' understanding of key terms and concepts that have been outlined in the chapters.

It is my hope that this book can take some of the fear out of statistics. I find that students often approach a statistics course as an unnecessary burden that they are forced to complete. I also find that they develop a strong appreciation for statistics over the duration of the course. Unfortunately, it is often one of the last courses they take for their social science major. Delaying statistics to the end of their undergraduate careers robs students of the opportunity to apply useful dimensions of knowledge and critical thinking skills to their studies. Not much that we do in social science departments prepares students for statistics, yet we often assume that students have a working knowledge of these concepts. Therefore, I suggest thinking of statistics as a "foundation" course that sharpens the analytical capabilities of students as they begin to move into upper-division courses. *Statistics and Data Analysis for Social Science* is written in that spirit.

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CHAPTER

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INTRODUCTION

The racial divide in American society is not universally recognized. What we consider to be real or not real is often a matter of personal experience and social standing. For example, one person might argue that racism does not exist in the United States because laws protect against racial discrimination, while another person argues that racism does exist because he or she has experienced it firsthand growing up in a community of color. Which claim is correct? While it is true that many laws do protect against acts of racial discrimination, it is also true that many communities of color have underfunded schools that can impose limits on their students' **life chances** after graduation. Institutionalized racism, such as underfunded schools in communities of color, can be difficult for residents of more privileged communities to comprehend.

Life chances: A phrase that Max Weber used in his analysis of social class to refer to differences in the likelihood of people from different class backgrounds having access to similar resources. Differential access to resources can lead to different opportunities (chances) in life. Opportunities to achieve personal goals originate in class standing. Higher class standing affords people greater life chances.

In fact, according to the U.S. Bureau of the Census (2018), in 2017 median household income among white non-Hispanic respondents was about $68,000 and among blacks was only about $40,000. This difference is not the result of chance. It reflects historical and institutionalized forms of discrimination (access to loans, education, jobs, and other pathways to upward mobility), not individual deficiencies. Thus, while one person may be correct in stating that racism does not exist because laws protect against it, another person might also be correct in stating that, despite such laws, racism does exist due to structural barriers to upward economic mobility.

Unlike a rock analyzed by geologists, it is impossible to go outside, pick up some racism, and bring it back inside to analyze. Yet we know it exists by looking for examples in our own lives or in academic literature. In his book *Sundown Towns* (2005), sociologist James Loewen documented the existence of hundreds of towns across the United States that banned blacks from being within the town limits between sunset and sunrise. Similarly, sociologist Robert Bullard has spent the better part of several decades documenting the tendency for communities of color to bear a disproportionate burden of ecological hazards relative to white communities (e.g., Bullard, 1993).

The question might not be "Does racism exist?" Instead, the question might be "Depending on how you define it, does racism exist?" Therefore, it is important to be careful in how we define concepts, particularly if we are going to use those concepts to collect and statistically analyze data from the world around us.

Table 1.1 contains some important terms and definitions that are used in this chapter.

This chapter focuses on some of the most important underlying ideas behind statistics. It lays a foundation on which we can move forward into actual statistical analyses. It is divided into three main sections: Concepts, Variables, and Measurement. Concepts are ideas that we think exist and that we hope to be able to effectively measure in the form of variables. Variables are characteristics of people, or other units of analysis, that vary from case to case. Measurement refers to the aspects that we must consider when creating variables and calculating statistics.

TABLE 1.1

Term	Definition
Variable	Anything that varies from case to case *or* a logical set of attributes
Attribute	A characteristic of a variable
Conceptualization	The process of defining what is meant by a variable
Operationalization	The process of creating an actual measure for a variable
Levels of measurement	Nominal, ordinal, and interval/ratio
Nominal variable	A variable for which the attributes cannot be ranked from high to low
Ordinal variable	A variable for which the attributes can be ranked from high to low but do not take numeric form
Interval/ratio variable	A variable for which the attributes can be ranked from high to low because they take numeric form
Mutually exclusive	A condition that exists when a case fits into one and only one attribute of a variable
Collectively exhaustive	A condition that exists when attributes of a variable exhaust all the possible values that cases may have
Validity	The degree to which a measure reflects the idea it was intended to measure
Reliability	The degree to which a measure yields consistent results across samples

CONCEPTS

The earth is round and not the center of the universe? Recently, several professional athletes and others have claimed that the earth is flat rather than round. No scientific evidence supports this idea, nor to the best of my knowledge has anyone walked off the edge of the earth. But 1,500 years ago, a debate emerged over whether the earth was flat. Imagine yourself in this world, a world where a significant number of people believe that the world is flat and that if ships sail too far toward the horizon they will drop off the edge of the earth. Other people believe that the earth is round and located at the center of the universe because the stars, moon, and sun appear to circle the earth. Without evidence, how do we determine who is right?

One day, a group of sailors who had left years earlier on an expedition return, claiming that they have sailed *around* the world. Sailing in one direction, they ended up where they began rather than falling off the edge. Of course, if one believes that the earth is flat, this claim is preposterous. For others, it reinforces the belief that the stars, moon, and sun circle the earth. It also raises the possibility that the earth is spinning and that it might not be the center of the universe. The movement of the stars might only give the illusion of the earth being the center of the universe. These are dangerous claims that challenge fundamental belief systems; some people were persecuted and killed for such beliefs.

Over the years, evidence builds to support the claim that by sailing continuously in one direction (say, west), a ship can in fact end up where it began. If the only way that a line can end up where it began is by going around, then the ship must have sailed around the world. This finding presented a serious challenge to the dominant understanding of the world and eventually led to new ideas regarding gravity, the laws of motion, astronomy, and even religion.

If the earth is round, why is it that ships sailing toward the horizon do not lift off the round earth and sail off into space? Something must keep them "stuck" to the earth—but what? Gravity. Gravity must keep ships attached to the round earth and prevent them from leaving the earth's surface and sailing off into space. The idea of gravity existed for about 1,000 years before Sir Isaac Newton published *Principia* (1848), but he is generally credited with developing some of the models that many scientists still use today.

Has anyone ever seen gravity? Has anyone ever touched gravity? No, of course not. Gravity exists at the conceptual level. Today, we believe that all objects are somehow attracted to one another because of gravity. We use these ideas to predict the motion of planets, the trajectory of comets, the presence of black holes, and the future of the universe. It is an idea that works well and can explain a lot of physics. Yet if we could jump forward in time, we might find that other concepts have come to replace our current concept of gravity.

In this example, gravity is a human construct that was a long time in the making; it is a concept or an idea that we use to help us make sense of the way the world works. **Concepts** are ideas that we think represent reality. Like our understanding of the earth and gravity, social science is based on the creation and analysis of concepts. Like gravity, racism, sexism, inequality, love, and hate all are examples of concepts. They do not exist in the sense that we can pick them up, weigh them, or put them under a microscope; however, we know that they exist because we live them every day. We experience them as real the same way that some people experience racism as a part of their daily life. Such is the stuff of sociological analysis.

Concept: An idea that we think represents something in the real world.

Scientific Revolutions

In his well-known book *The Structure of Scientific Revolutions* (1962), philosopher Thomas S. Kuhn (1922–1996) referred to the shift from believing that the world is flat to believing that the world is round as a scientific revolution. Scientific revolutions occur when old understandings of the way the world works are replaced with new explanations. Kuhn argues that people tend to think of science as a slow accumulation of knowledge over time. This gradual accumulation of knowledge is incorporated into increasingly sophisticated models of how the world works that are then used to pursue a more informed knowledge of reality. Many people believe that this scientific "progress" is the way to find the truth that lies behind our misunderstandings of the universe.

Kuhn (1962) argued that the search for "truth" is misguided. He and many others argued that we never find the truth, but we do develop better and more sophisticated understandings of the world around us—an understanding that we should anticipate will someday be challenged. For example, when the "flat earth" theory is challenged to the point of not working, a scientific revolution takes place in which old interpretations of the world are replaced with new ones. Given our relatively limited investigations into these topics, why should we expect that our new model will be the final one? It is simply the best we have at the time; but it too will most likely change.

Kuhn's model of science is still applicable today. While the world around us exists physically, and many of our ideas about how it works seem to work quite well, our understanding of it is based on imperfect models and, often, flawed interpretations. In other words, the concepts developed to make sense of our surroundings often have shortcomings. Nevertheless, scientists use the best models available to them at the time until a new model is developed that does a better job. We refer to scientific eras when a single model of the world dominates other possible understandings as times of "normal science." The problem with these times is that anomalies tend to arise. **Anomalies** are scientific findings that cannot be explained by the dominant model(s) of the time.

Anomalies: Phenomena that are not explained by existing models of understanding.

Take the example of learning that the world is not flat. A ship sailing around the world is an anomaly because it never should have happened if the world is flat. The ship should have fallen off the edge of the world, not returned to its point of origin. The events do not fit the current model of the earth, and they challenge us to find a new model with which to understand the world and reconsider our current astronomy. Similarly, an airplane flying around the world in one direction (say, east) should never come back to its point of origin. I have yet to hear the flat earth theorists' response to this anomaly in their logic.

A small number of anomalies do not lead to an overhaul of a system of logic and beliefs. It may be that those proclaiming the anomaly are persecuted for their beliefs or that the anomaly itself was a misinterpretation of events. How many anomalies it takes to necessitate a change in the current paradigm is often a question of politics and power more than it is a question of legitimacy (particularly when religious beliefs are challenged). Let's just say that when enough evidence is accumulated to offer support for the claim that the world is not flat, a scientific revolution takes place in which old understandings are jettisoned for new models that work "better." Following is

a box titled *Now You Try It*. These boxes are located throughout each chapter and are intended to provide readers with opportunities to check their understanding of the concepts as they are presented. The answers to the Now You Try It exercises are located at the end of each chapter. We now turn our attention to a sociological concept that seems to be withstanding the test of time.

NOW YOU TRY IT 1.1

Here is an exercise that may help you to realize just how much we take the world for granted. Have you ever stopped to wonder about the location of the moon in the night sky? The answer to the question posed below can be obtained in a couple of ways: quickly (by looking at the end of this chapter) or slowly (by gathering data over the next several days).

Most people know where the sun rises and where it sets. The sun rises in the east and sets in the west. But most people do not know where the moon rises and sets, or where the planet Saturn rises and sets, or where any heavenly body rises and sets for that matter. So where does the moon rise and where does it set? Can you offer a logical explanation for your answer?

Emile Durkheim, Structural Strain, Suicide, and Anomie

Let's leave the world of physics and turn to a sociological example of concepts. In 1912, Emile Durkheim (1858–1917) became the first person to ever hold the official title of "sociologist" at a university (at the Sorbonne in Paris). Although he studied and wrote on several sociological topics, including the division of labor, religion, education, and social control, he is best known for his studies of suicide. Astute in the power of statistics, Durkheim poured over thousands of government documents to try and make sense of variations in suicide rates over time and across nations. He found that suicide is a normal part of all societies. What intrigued him, however, was how the rates of suicide change; sometimes they are high, and other times they are low. Ultimately, one of his conclusions was that during times of great uncertainty, or what we might think of as times of normlessness, suicide rates go up. He called this state of normlessness **anomie**.

Anomie: A societal condition in which the normative standards of behavior are unclear.

Durkheim's concept of anomie is one example of a sociological concept that has withstood the test of time, a concept that he used to help better understand changes in suicide rates. And it appears that Durkheim's concept of anomie may be just as applicable today as it was during the early part of the 20th century when he developed it.

Sociologists have studied suicide for about a century. We know that in 2016 the suicide rate in the United States was about 14, meaning that about 14 of every 100,000 people took their own lives. In that year, about 600,000 other people were admitted to emergency rooms for self-inflicted injuries (Xu, Murphy, Kochanek, Bastian, & Arias, 2018). Of these people, males between the ages of 16 and 26 years and males over the age of 70 years are two of the demographic groups most likely to commit suicide. Why males? Why males of these age ranges? And why higher rates of suicide in places like Alaska, Montana, Wyoming, and New Mexico? These are questions that require the use of concepts. We know the numbers, but we can't explain them without using concepts.

The suicide rate is significantly higher for men than it is for women (more than three times higher), a trend that holds true nationally and in every state. This raises interesting questions regarding differences in how males and females think about suicide and how they act on those ideas.

Durkheim is often noted for his contributions to our understanding of the conditions in which different kinds of suicide are most likely to occur. He analyzed historical data on the number of suicides from one year to the next. Among other trends, he found that males were more likely to commit suicide than females and that Protestants were more likely to commit suicide than Catholics. Why? He referred to certain characteristics of groups or communities as "social facts." In other words, he believed that social forces exist externally from individuals and that these forces "push" and "pull" individuals into predictable patterns of behavior, including patterns pertaining to rates of suicide.

Durkheim was fortunate to be a contemporary of other well-known sociologists such as Karl Marx (1818–1883) and Max Weber (1864–1920). This allowed Durkheim to combine his own ideas with those of his contemporaries, particularly ideas about the workings of capitalism and the impact that capitalism may have on people. He theorized that all people are inherently social beings and that humans need one another to (1) survive materially and (2) set limits on our worldly desires. He argued that without a society to set normative standards for the accumulation of wealth and other worldly possessions, the capacity for humans to constantly want "more" would be endless. This is important because, as Max Weber showed in his famous book *The Protestant Ethic and the Spirit of Capitalism* (2004), the confluence of the Protestant ethic (hard work, frugal living, and reinvestment as a way to accumulate wealth to demonstrate one's worth to God) and the spirit of capitalism (an ever-expanding economy with seemingly limitless capacity for growth) created the very conditions in which vast quantities of material wealth can be generated.

Anomie Then. Analyzing how suicide rates vary over time and from one society to the next, Durkheim (1897/1951) concluded that people were more likely to commit suicide during times of uncertainty, for example, during economic depressions. Out of this finding, he developed his concept of anomie. Anomie is a condition in society that increases when the established rules and regulations of society become blurred or no longer seem to apply. An example of this is a questioning of the belief in free market economies during times of economic crisis. Economic downturns challenge our faith in capitalism, and a rising level of anomie characterizes society. When rules become less clear, or in the absence of rules, people are more likely to suffer as their society is increasingly characterized by a state of pathological anomie (unhealthy or extreme levels of anomie). It is during these times that Durkheim detected increased rates of suicide.

At particular risk of suicide during times of economic slowdown are males and Protestants. Higher societal expectations for economic success among males can result in greater levels of anomie among males during economic recessions because they are more likely to experience declining social status. Similarly, because the accumulation of wealth has greater religious significance to Protestants than to Catholics (according to Weber), economic downturns can create the belief of less favorable outcomes in the afterlife (going to heaven) and generate greater levels of anomie. Therefore, we can predict and explain higher suicide rates among males and Protestants during times of economic decline. And Durkheim's concept of anomie remains particularly useful for explaining the high rate of suicide among young men today.

Anomie Now. A recent article in *Newsweek* magazine, based on the work of sociologist Michael Kimmel (who published a book titled *Guyland* [2008]), noted that American males between the ages of 16 and 26 years have one of the highest rates of suicide in the country (Newsweek Staff, 2008). It is interesting that this rate seems to coincide with an era of extended juvenile behavior for this group. The 20-something men of the late 1990s and early 2000s are much more likely to be extending their college party lifestyle for an additional decade or more than did any of their historical counterparts. The rise in suicide rates and the delay of life course changes may be related and explained sociologically.

Consider the effects of a long-term chronic economic downturn relative to a sudden stock market crash. A 30-plus-year contraction in wages, limited opportunities for upward mobility, and declining labor force status relative to females have created the conditions in which male college graduates face one of the toughest job markets in history. This newfound challenge to upward mobility flies in the face of the cultural definitions of what it means to be male. As the relative social status of young males declines over time, a disconnect emerges between expectations and reality. This could explain the social context in which rising levels of anomie come to characterize the population of young males. As the societal norms of "maleness" are increasingly blurred by the economic downturn, suicide rates are likely to increase.

Some sociologists have noted that mass media corporations are capitalizing on the newfound status of young males by promoting a culture that endorses partying, lack of responsibility, and objectification of women (Kimmel, 2008). Young males appear to be victims of the strain that results from having high societal goals for achievement (high income, material wealth) without the means (strong

job markets, expanding economy) to reach them. Consequently, they are more likely to turn to media portrayals of what it means to be male as cues for their own behavior and worldviews.

To summarize, Durkheim, like all scientists (chemists, physicists, biologists, botanists, psychologists, sociologists, and others), looked for patterns. On identifying a pattern, the goal is to explain it. To do so, he developed the concept of anomie. It is not the only way to explain suicide or the rise of new definitions of "maleness," but it is an interesting one.

New models of the way the world works enable us to make sense of our surroundings, but these models are often based on highly abstract ideas like anomie. While this is not necessarily a problem, it does require scientists to remain relatively open-minded about the possibility of flaws in their models. Identifying and explaining patterns among variables is a difficult and often abstract process. After all, the next scientific revolution is always on its way.

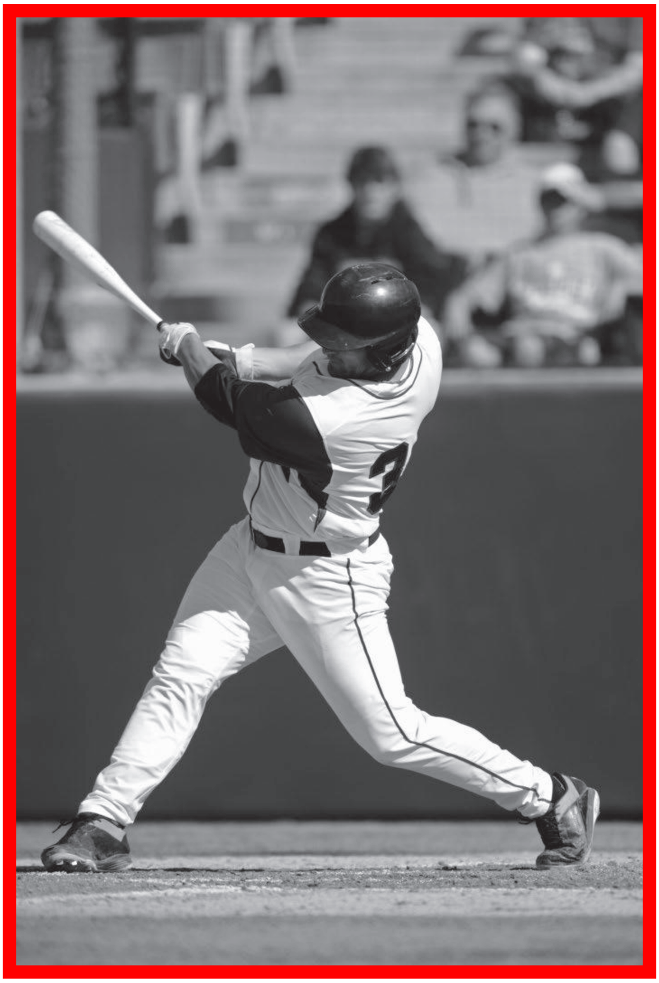
WHY STATISTICS?

How do **statistics** contribute to our understanding of the world? Why should students take an entire course on statistics? These are good questions for which there are some good and some not-so-good answers. The not-so-good answers tend to go something like this: "It is required for the degree," "I had to take it, so should you," and "You can't be a good social scientist without statistics." In fact, you can be a very good social scientist without statistics, but you can be even better with some basic statistical tools at your disposal. This brings us to the good answers to the question "Why statistics?"

Statistics: Numeric representations of reality that facilitate our ability to describe, communicate, predict, and act. They describe characteristics of a sample.

For better or worse, we live in a world of statistics, statistical reasoning, and decisions based on statistics. In the most fundamental sense, statistics are numerical representations of reality. They are indicators. Often they are valid representations, and other times they are not. It depends on the quality of our research methods. Statistics are used to describe conditions (such as average income), communicate more effectively (baseball fans understand the meaning of a .300 hitter) and predict outcomes (such as the likelihood of a baseball player getting a hit), and develop policy (such as whether a drop of 3,000 points in the Dow Jones Industrial Average warrants a financial bailout package). In this sense, statistical knowledge at the individual level provides deeper insight into the kinds of forces that make the world what it is.

In his widely acclaimed book *Damned Lies and Statistics* (2001), sociologist Joel Best argued that there are several kinds of statistics "consumers" in the world: the Awestruck, the Naive, the Cynical, and the Critical. Best defined the Awestruck as those who fail to think critically about statistics and are likely to believe what they hear about a statistic (p. 162). The Naive consist of those who are "basically accepting" of statistics because they tend to feel that most people, including statisticians, are sincere (pp. 162–163). The Cynical are those who tend to reject statistics on the basis that they amount to nothing more than sophisticated lies that are generated out of particular interests (p. 164). Finally, Best discussed the Critical consumers as people who understand that every statistic is a complex way of conveying information. They tend to know something about statistics, and they tend to know what kinds of questions to ask to clarify confusion or misleading statements (pp. 166–167).



The purpose of taking a statistics course is not to learn how to calculate a bunch of different statistics, although we should learn that too. Instead, the goal is to increase the range of analytical tools at our disposal to understand and live in the world with which we are confronted. It is to learn to think critically and reflectively about what others tell us about the world so that we can come to our own well-informed conclusions. In this sense, statistical literacy is no different from other types of literacy (language, computer, financial, etc.) or skills (driving, cooking, home repair, etc.) that we need to navigate our daily routines.

The goal of this book is to provide students with an introduction to some of the most important statistical concepts (central tendency, dispersion, probability, and association) and how they can be applied to the problems of our day. Real-world examples and data are used as much as possible to try and convey the manners in which these tools and skills can be applied. Examples with step-by-step calculations are included. Finally, the book is based on the belief that by working through some calculations, students will be more likely to grasp how statistics are calculated and how to use them more effectively.

VARIABLES

Conceptual Definitions of Variables

Scientists work with *variables*. A big part of scientific analysis is (1) describing how cases are distributed, (2) describing how variables interact, and (3) making predictions. This is true for both the natural and social sciences. For the most part, very few constants exist in science, and really no constants exist in the social sciences. According to astrophysicist Neil DeGrasse Tyson's twitter feed (February 5, 2016), "In science, when human behavior enters the equation, things go nonlinear. That's why Physics is easy and Sociology is hard." Everything varies from case to case. As we move from one person to the next, sex, age, hair color, education, and food preferences all vary. This is true when we compare individuals, and it is true when we compare families, communities, cultures, and any other *unit of analysis*. Two common ways of thinking about variables are (1) things that vary from case to case and (2) logical groupings of *attributes*.

Units of analysis are scientists' objects of analysis, or who or what is being studied. **Variables** are defined here as things that vary from one case to the next. For example, the sex of a respondent in a survey can vary between males and females. Those same variables are the building blocks of scientific research. **Attributes** are defined here as a set of logical characteristics for a variable. Logical groupings of attributes constitute variables. For example, the attributes *male* and *female* constitute the variable *sex of respondent*.

Units of analysis: The who or what that data describe and that tend to consist of individuals or groups/places (towns, schools, teams, etc.).

Variable: Anything that may vary from one case to the next (sex, height, level of education, etc.).

Attributes: A logical set of characteristics for a variable.

In social science, variables can measure ideas or physical attributes. Physical attributes are easy to comprehend. For example, we might want to describe the members of a college sports team. The players' height, weight, age, and sex all are easily described variables. We might then want to describe the players' overall academic success. To do this, we might check their SAT exam scores, their overall grade point average (GPA), or whether they have made the dean's list. But do any of these really give us a true reflection of their level of academic success? Maybe, but some ideas are harder to measure than others.

Take the concept of *hate*. Hate exists only at the conceptual level. It is not a physical reality, although it has very real consequences. We might see examples of actions that we feel are motivated by hate, such as gay bashing, shouting racial slurs, and genocide, but we still cannot pick up the hate, put it on a scale, and measure it. How do we measure the amount of hate in one society relative to another society? We must first define exactly what we mean by *hate* and then attempt to find ways to measure it. After we have measured it in some methodologically valid and reliable manner, we can describe its characteristics statistically.

In Durkheim's analysis of suicide, the unit of analysis is societies (which Durkheim defined very loosely), while anomie and suicide are variables (because they vary across time and place). The level of anomie in any given society changes over time, and the level of anomie tends to vary from one society to the next. Anomie, like hate, is not something that can be seen with the naked eye, yet it seems to be a reality because it makes sense logically and is supported by historical data. "Seeing" anomie requires abstract thought and theoretical understanding. And as you may have already guessed, debates over how to measure concepts like anomie, which may or may not exist, are common.

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Independent and Dependent Variables

Independent variable: The variable that is controlled or held constant in a hypothesis.

Dependent variable: The variable that is influenced by changes in the independent variable.

Direction of effect: The part of a hypothesis that predicts whether two variables are positively or negatively associated.

Hypothesis: A prediction about the distribution of a variable or the association between two variables.

Statistical association is discussed in much greater detail in Chapter 8; however, it is briefly introduced here. The idea behind statistical association is covariation, or the idea that a change in one variable is often accompanied by a change in another variable. Often one is called the **independent variable** and the other is called the **dependent variable**. We might predict (or hypothesize) that a change in one variable, such as education, is associated with a change in another variable, such as income. When we say that education and income are associated, we are hypothesizing (making an educated guess or an informed prediction). To use more scientific language, we *hypothesize* that education and income are positively associated. The positive wording refers to the **direction of effect**. This means that we predict that increases in education are accompanied by increases in income. A negative direction of effect would exist when increases in education are accompanied by decreases in income.

In this example, education is the independent variable and income is the dependent variable. In other words, our assumption is that a respondent's income is, at least partially, a result of how much education the respondent has. A good way to remember which variable is independent and which one is dependent is to phrase the **hypothesis** in an "if . . . , then . . ." format. This implies a temporal order of events, for example, "If education increases, then income increases." In this format, the independent variable always follows the *if* and the dependent variable always follows the *then*.

It is important to note that an association between two variables does not mean that changes in the independent variable *caused* changes in the dependent variable. Scientists use the phrase "association does not imply causation" to emphasize this fact. Just because people with higher levels of education may have higher incomes does not necessarily mean that their education caused them to have higher incomes. To effectively argue that two variables are associated, three criteria must be met:

1. The cause must precede the effect. This means that we would need to show that higher levels of education came before higher incomes as opposed to higher incomes preceding higher levels of education. This could be very difficult to show because people with higher incomes can afford higher levels of education.
2. Changes in the dependent variable must be the result of changes in the independent variable and not some preceding or intervening variable(s). In other words, it is possible that higher levels of income could be the result of any number of factors, one of which may be education.
3. The association must be present "often enough." This means that we may find cases in which education and income are not associated; however, a few cases do not threaten the overall trend. The question then becomes *How often must the prediction hold true?* This is a tricky question and represents a point at which science often becomes political and the subject of debate.

Operational Definitions of Concepts

In thinking about concepts and variables, it is useful to think chronologically. Defining what we mean by an idea must precede devising ways to measure our idea. Describing or defining an idea that we think represents something in the real world is a process called **conceptualization**. Devising ways to measure the ideas we have conceptualized is called **operationalization**.

Conceptualization: The process of defining what we mean by a concept.

Operationalization: The process of developing a variable that measures a concept.

When we take an idea and define what exactly we mean by it, we are conceptualizing. For example, when we take the concept of income and conceptualize it, we might refer to the amount of money a person makes at a given job in a given year. Or we might refer to the amount of money people make at their jobs added to the amount of money they earn from investments. Either technique is a valid way to conceptualize income. It is important to convey these conceptual definitions to those reading and using our findings.

When we take an idea, a concept, and devise a measure with which to compare one case with the next case, we are operationalizing a variable. For example, we might conceptualize income to refer to the amount of money a person makes at a given job in a given year, but this leaves several possibilities open. The variable might refer to the actual dollar amount a person makes (such as $32,515), or it might refer to a range of income ($0–$19,999, $20,000–$29,999, $30,000–$39,999, etc.). In other words, there is no right or wrong way to operationalize concepts into variables (it depends more on what we want to know). Even so, sometimes one way proves to be more useful and valid than another way.

Most social scientists probably believe that anything can be measured (alienation, class conflict, anomie, etc.), but only recently have they had access to the kinds of technological resources to gather, analyze, and communicate data that we now have at our disposal. Social scientists claim that anything can be measured, even concepts (ideas with no "real" existence). So why couldn't we measure something as abstract as Marx's concept of alienation or Durkheim's concept of anomie?

Alienation. Marx argued that capitalism is a mode of economic production based on conflict between two classes of people: capital (aka the bourgeoisie) and labor (aka the proletariat). Class membership is determined by one's relationship to the means of production. Capital owns the means of production and labor does not. At work, members of the labor class sell their ability to do work (their labor power) to capital in exchange for a wage rate. Marx claimed that this has the effect of alienating people from their labor because individuals no longer control their labor, nor do they control the products of their labor.

Alienation: A condition in which people suffer from a "disconnection" between themselves and their work and disconnection from one another.

Logically, this makes sense; however, can we measure **alienation** in some way to offer empirical evidence that it exists? As in the case of Durkheim's *anomie,* Marx's *alienation* exists at the conceptual level. Can you think of ways to operationalize alienation?

You might not care very much about what you do for work as long as you make enough money. On the other hand, you might prefer to sacrifice some income for work that gives you a great deal of satisfaction, meaning work that is less alienating. From this, we might surmise that people who like the type of work they do are less alienated from their labor than people who do not like the type of work they do.

Although we cannot pick up alienation and put it on a scale to see how much of it a person experiences, we can ask people whether they are likely to stay at a job for the income or to sacrifice some income for a job they like. Those who indicate that they would be willing to take less pay but have a job they like would be those experiencing lower levels of alienation. In this way, we have taken the concept of alienation and operationalized it as a variable.

> Would you be willing to take a pay cut to have a job that you enjoy more than your current job?
>
> Yes
>
> No

One problem that arises with this variable is that it has a class bias embedded within it. In other words, people who don't make enough money to make ends meet are much more likely to answer "No." Therefore, we could only compare the answers from those respondents of relatively similar class standing. We could argue that those who answer "Yes" are experiencing greater levels of alienation from their work than those who answer "No."

Several factors must be considered when operationalizing a variable. Two of these are that the variable must be (1) collectively exhaustive and (2) mutually exclusive.

Collectively Exhaustive. We cannot say that a variable is operationalized correctly unless the attributes of that variable are collectively exhaustive. Attributes are **collectively exhaustive** when an attribute exists for every possible case.

Collectively exhaustive: A necessary condition for variables that is met when the attributes of a variable include every possible response.

Example: Attitude Toward the Quality of City Parks

Suppose we are conducting a study of city parks and we want to find out how people of different racial backgrounds feel about the quality of parks in different neighborhoods. We might have only enough resources to sample 100 respondents. In our random sample, we expect the sample to break down as indicated in Table 1.2.

It is possible, however, that we have a respondent from Cape Verde who does not feel that any of our categories of race are applicable to him or her. How do we handle cases like this?

Statistically, 100 respondents could be an insufficient number of respondents on which to claim that we have statistically significant results, particularly if we operationalize the variable in a way that allows some attributes to contain very small numbers of respondents such as one Cape Verdean. Therefore, instead of having an attribute for each ethnicity, we might operationalize our variable as White, African American, and other. Our data might then look like Table 1.3.

TABLE 1.2

How do you identify yourself?
White – 50%
African American – 35%
Native American – 5%
Asian – 5%
Latino – 5%
Total 100%

This attribute of *other* allows us to make the variable collectively exhaustive, leaving no one out. It does, however, have the effect of "glossing over" potentially important subtleties in the data by failing to differentiate Native Americans, Asians, Latinos, and Cape Verdeans.

TABLE 1.3

How do you identify yourself?
White – 50%
African American – 35%
Other – 15%
Total 100%

If we are concerned about being able to generate statistically significant results for Native Americans, Asians, or Hispanics, we must then sample a larger number of respondents. Then we can change the attribute *other* to *Native American, Asian, Latino, Cape Verdean, or other*.

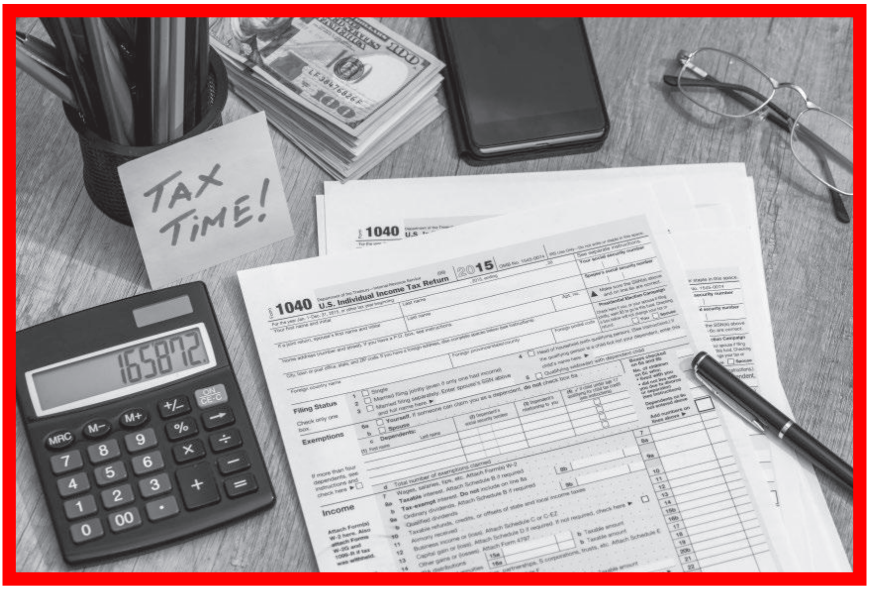


TABLE 1.4

Pre-tax Income (2005)	Pre-tax Income (2005)
___ $0–$10,000	___ Less than $10,000
___ $10,000–$40,000	___ $10,000–$39,999
___ $40,000–$60,000	___ $40,000–$59,999
___ $60,000 and higher	___ $60,000 and higher

TABLE 1.5

Pre-tax Income (2005)
___ $0–$20,000
___ $20,000–$40,000
___ $40,000–$60,000
___ $60,000–$80,000

Mutually Exclusive. We cannot say that a variable has been operationalized correctly unless the attributes of that variable are mutually exclusive. Attributes are **mutually exclusive** when they do not overlap each other. For example, we might ask people to tell us what their annual pre-tax income is by placing an X on the appropriate line.

Mutually exclusive: A necessary condition for variables that is met when each case can be applied to only one attribute of a variable.

As you can see in Table 1.4, there is a problem with the variable on the left. What if respondents make $10,000, $40,000, or $60,000 exactly? How should they answer? The problem is that the variable in the box on the left is not operationalized such that the attributes are mutually exclusive. The box on the right is operationalized such that the attributes are mutually exclusive.

Table 1.5 has two problems. Can you explain what is wrong with it? First, the attributes are not collectively exhaustive. It is possible, and even likely, that in our sample we will find at least one respondent who makes more than $80,000 per year. There is no attribute in our variable for such a respondent to indicate this to us.

The second problem deals with mutual exclusivity. As you can see, a person making $10,000, $40,000, or $60,000 could respond to either of two attributes. It is vital that statisticians be aware of the sources of their data to avoid these kinds of problems. A common saying in statistics is "garbage in, garbage out." This means that if the data used to generate statistics are not methodologically sound, then the statistics generated by those data are not representative of reality.

Remember that all variables must be operationalized such that the attributes are both collectively exhaustive and mutually exclusive. When variables do not meet these two requirements, data must be considered unreliable and invalid. Consequently, the statistics generated from such data must be considered suspect and nonrepresentative of the concepts they are intended to represent.

MEASUREMENT

Levels of Measurement

Levels of measurement: The degree of mathematical precision that can be applied to a variable. The three levels of measurement are referred to as nominal, ordinal, and interval/ratio.

Now that we have seen how social scientists are able to measure practically anything, provided the concept is operationalized in a valid and reliable manner, we can discuss **levels of measurement**. As with most tasks in life, there is more than one way to get it done and, as you might have guessed, there is more than one way to operationalize a variable.

For example, if I ask you if you like chocolate, you could answer *yes* or *no*. If I ask you how much you like chocolate, you could answer from the following list: *not* *at all, a little,* or *a lot*. Or I could have you indicate on a scale of 1 to 100 how much you like chocolate. A fundamental difference exists between these ways of measuring. One way elicits responses that cannot be ranked from high to low, and the others elicit responses that can be ranked from high to low. In the case of ranking from 1 to 100, we can even count how far from 0 a person likes chocolate.

These are the three levels of measurement: nominal, ordinal, and interval/ratio. All variables can be categorized into one of these three levels, although sometimes the differences are not so clear. It is extremely important to understand the different levels of measurement and how to identify the level at which a variable is operationalized. The statistics that can be used to describe a variable depend on the level at which the variable is operationalized. In other words, if a variable is operationalized at the nominal level, only certain statistics can be used. For example, as discussed in Chapter 3, measures of central tendency (mean, median, and mode) are statistics used to describe where cases tend to cluster in a distribution. In the case of a nominal variable, only the mode can be used; however, in the case of an ordinal variable, both the mode and the median can be used. The following briefly describes each level of measurement and explains how the measurements differ.

Example: Degree of Religiosity

Nominal. **Nominal** variables have attributes that cannot be ranked from high to low. The attributes are nothing more than different categorical responses. For example, male or female as attributes to the variable of *sex*. Male is not more or less than female, and female is not more or less than male. Similarly, we have the example of religiosity.

Nominal: Variables operationalized at the nominal level have attributes that cannot be rank-ordered.

Suppose we ask 100 people whether Jesus (or any other religious figure) is part of their religiosity and get the results in Table 1.6. This does not mean that the people who answered "Yes" are more religious. People who answered "Yes" are not necessarily more or less religious than people who answered "No"; it is just that some people have Jesus as part of their religiosity and some people do not. Therefore, the attributes cannot be ranked from high to low or from more to less. They simply indicate a difference between two groups of people.

TABLE 1.6

Is Jesus part of your religiosity?
Yes – 50%
No – 50%

Ordinal. **Ordinal** variables have attributes that can be ranked from high to low, but the "distances" between the attributes can't be measured. For example, consider a questionnaire that asks how much you like chocolate ice cream. Your choices are "a lot," "somewhat," and "a little." A person who indicates he or she likes chocolate ice cream a lot obviously likes it more than someone who likes it a little. Yet we cannot measure exactly how much more the first person likes it.

Ordinal: Variables operationalized at the ordinal level have attributes that can be rank-ordered, but those attributes do not reflect actual numeric values.

In the religiosity example, we see the same kind of logic. Suppose our data yield the results in Table 1.7. Some people's belief in Jesus is "not strong," others' belief is "somewhat strong," and still others' belief

TABLE 1.7

How strong is your belief in Jesus?
Not strong – 33%
Somewhat strong – 34%
Very strong – 33%
Total – 100%

is "very strong." Therefore, we know that a person who answers "very strong" has a stronger belief in Jesus than someone who answers "not strong." But how much stronger is it? We don't know because we have no way of measuring the "distance" between "not strong" and "very strong." We can rank-order our respondents from high to low in their belief in God by placing them into one of the three attributes, but we have no way of addressing the question of how much stronger or weaker one respondent's belief is than the next.

Interval/ratio: Variables with attributes based on real or relative numeric values (meaning the attributes can be rank-ordered and used to conduct mathematical calculations).

Interval/Ratio. **Interval/ratio** variables have attributes that can be both ranked and measured numerically. Attributes take the form of specific numbers, often with specified units of analysis. For example, the number of tackles that a football player has in a game varies from player to player. One player may have five tackles and another player has seven. The second player has more tackles *and* we know exactly how many more.

The same logic holds true for our measure of religiosity. When we ask respondents to tell us how many times they attend religious services in a month, they answer with a numeric amount. If one respondent attends religious services four times each month and another attends one time each month, we know that the difference is three. Respondents who attend more often are considered more religious; therefore, the first respondent might be considered to have four times the religiosity as the second respondent. Not only do we know that the first respondent attends religious services more often, we know exactly how many more times.

Interval and ratio variables differ, but they are treated the same statistically—that is why they are lumped into the same category. The difference between interval and ratio variables is that ratio variables have a true zero point, while interval variables have an arbitrary zero point. For example, if I ask you how many skateboards you own, and you say zero, then you do not own any skateboards. This is a ratio variable with a true zero. If I ask you how you rate the mayor on a scale of –10 to +10 and you say 4, then you have some approval of the mayor. Had you answered 1, you still would indicate some approval, but not as much as someone who answered 4.

The 0 on the scale of –10 to +10 is an arbitrary zero. The same is true for a temperature of 0 degrees. On the Fahrenheit scale, 0 degrees represents an arbitrary zero. It is an arbitrary point on a thermometer that happens to be 32 degrees below the temperature at which water freezes. On the Celsius scale, 0 degrees happens to be the temperature at which water freezes. This is an arbitrary point (why wouldn't we consider zero to be the point at which some other liquid freezes?). On neither the Fahrenheit scale nor the Celsius scale does 0 degrees represent the absence of heat.

Regardless of the level at which variables are operationalized, the attributes of all variables must be both mutually exclusive and collectively exhaustive.

Below is an example using a question that is often used for course and instructor evaluations. As this example shows, any concept can be operationalized in a number of ways. In the first technique, we have a *yes* or *no* question (a nominal variable). In the second, we incorporate the concept of degree (an ordinal variable). And in the third, we incorporate the concept of degree in a measurable manner (an interval/ratio variable). Each of these represents a different level of measurement.

Example: Course Appreciation

Variables can be conceptualized and operationalized in any number of ways.

Nominal: Did you find the course worthwhile? Yes / No

Ordinal: How worthwhile was the course? Not at all / Somewhat / Very

Interval/ratio: On a range of 0 to 100, how worthwhile was this course? ____

When gathering data, it is generally a good idea to collect the data at the highest level possible. For example, suppose you are doing research (a survey) on GPAs. You could ask respondents to circle which category their GPA falls within, as given in Table 1.8. Or you could have respondents simply write down their GPA.

Example: Surveying Student Grade Point Averages

What is your GPA? ____

The advantage to having respondents write down their GPA, say it is 3.22, is that it allows you to see exactly what each respondent's GPA is. In other words, if you use the ranges in Table 1.8, you "gloss over" what could be important aspects of the data. For example, it could be that an important "cutoff" point in the data is 2.25, not 2.00, but by operationalizing it as in the table, this important trend might never be detected. In addition, if you ask respondents to indicate their GPA, you can always go back and categorize it according to any grouping you desire.

TABLE 1.8

Grade point average
0.00–1.00
1.01–2.00
2.01–3.00
3.01–4.00

INTEGRATING TECHNOLOGY

Statistical software programs allow researchers to *manipulate* data. Despite the negative connotation associated with the word *manipulate,* there is nothing ethically questionable about data manipulation. The term refers to the process of sorting cases, selecting particular cases, and other similar processes that allow for more detailed and effective statistical analysis of data. One common type of data manipulation is called “recoding.”

When data are collected and entered into a computerized database, they contain numeric codes, for example, Male = 1 and Female = 2. In the case of nominal and ordinal variables, the codes do not reflect actual value; they simply allow us to enter 1s and 2s into a database instead of typing out “Male” and “Female.” In the case of ratio (and often interval) variables, however, codes do reflect real values. For example, the number of years of education someone has might be 16. In this case, the number 16 is entered into the database.

Suppose we wanted to compare two different groups of respondents defined on the basis of whether or not they completed 12 years of education so that we could compare their income levels. By manipulating the data, we can quickly and easily create two groups of respondents: one group with less than 12 years of education and one with 12 or more years of education. We can assign a value of 1 to all respondents with less than 12 years of education and assign a value of 2 to all respondents with 12 or more years of education. In doing so, we essentially created a new variable by taking an interval/ratio variable and turning it into an ordinal variable. We know that every respondent in the second group has more years of education than any respondent in the first group, but we do not know the exact difference between any two respondents. This is *recoding.*

Data can be recoded only from higher-order levels of measurement to lower-order levels of measurement. In other words, we can recode interval/ratio variables into ordinal or nominal variables; and we can recode ordinal variables into ordinal variables with fewer attributes or into nominal variables. We cannot, however, recode in the other direction—nominal to ordinal variables or ordinal to interval/ratio variables. Therefore, it is important to try and collect data at the highest level of measurement possible because it provides a greater range of analytical possibilities later.

Take the example of attitudes toward gun control. As Table 1.9 shows, gun control can be operationalized as a nominal, ordinal, or interval/ratio variable.

TABLE 1.9 Gun Control as a Nominal, Ordinal, and Interval/Ratio Variable

Nominal	Ordinal	Ratio
Should your state have stricter gun control laws?	How important are stricter gun control laws to you?	On a scale of 0 to 10, how important are stricter gun control laws to you?
Yes	Very important	Respondent indicates a number.
No	Somewhat important	
	Not important	

GRAPHICAL REPRESENTATION OF DATA (WHAT DATA "LOOK" LIKE)

As we move from interval/ratio, to ordinal, to nominal levels of measurement, more and more information is lost and the range of statistical techniques that can be applied to the data diminishes. Therefore, it is usually a good idea to collect data at the highest level possible, the interval/ratio level, and then consider recoding the data into ordinal or nominal variables later. This, of course, is a methodological consideration as much as it is a statistical consideration. While it is usually possible to recode downward (interval/ratio to ordinal to nominal), it is never possible to recode upward (nominal to ordinal to interval/ratio). The three charts discussed below show how responses can be presented graphically.

Pie Charts. Figure 1.1 is called a pie chart. **Pie charts** are common ways of presenting data for nominal or ordinal variables. Remember that the attributes of nominal variables cannot be ranked from high to low. In this example, an argument could be made that if all the respondents were from the same state, the attributes could be ranked in some kind of high to low ordering. Often what seem like clear-cut differences between nominal and ordinal variables turn out to have many more "shades of gray" than first appear.

Bar Charts. Figure 1.2 is called a bar chart. **Bar charts** are often used for ordinal variables because they show trends in a variable. As this chart shows, respondents are more likely to feel that gun control is important or very important than not important.

Histograms. Figure 1.3 is called a histogram. **Histograms** are generally used to represent interval/ratio data. The height of each bar in the histogram is proportionate to the number of respondents for each response. Unlike bar charts, histograms show all the data for all responses without groupings and are used to show patterns for interval/ratio variables.

Just as some types of charts are more or less appropriate for visual representations of data, the same is true for statistics. Remember that statistics are nothing more than numeric representations of data that allow us to describe, summarize, and communicate information. Therefore, data collected at different levels of measurement (nominal, ordinal, and interval/ratio) are appropriate for different types of statistics. In Chapter 3, we turn our attention to a group of statistics called *measures of*

Pie chart: Often used with nominal and ordinal variables, pie charts consist of a circle cut into "pie slices" that add up to 100%. Each pie slice represents an attribute for the variable.

Bar chart: Often used with nominal and ordinal variables, a series of bars represent the different attributes of a variable. The height of each bar reflects either frequencies or percentages for each attribute.

Histogram: Used with interval/ratio variables. The height of each bar represents the frequency of each attribute.

FIGURE 1.1 Pie Chart With Frequencies

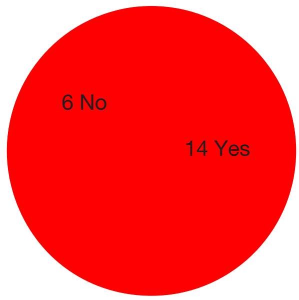


FIGURE 1.2 Bar Chart With Frequencies

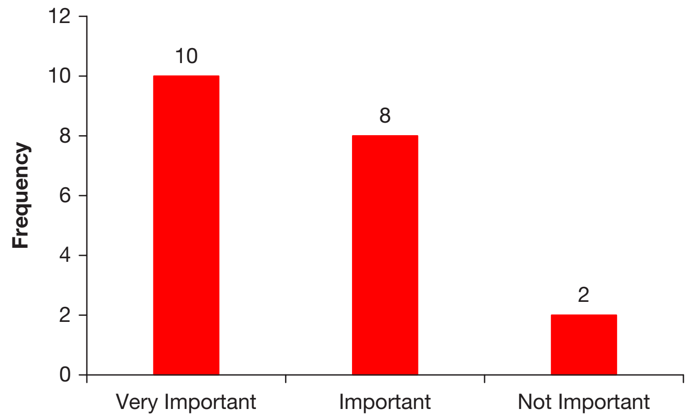
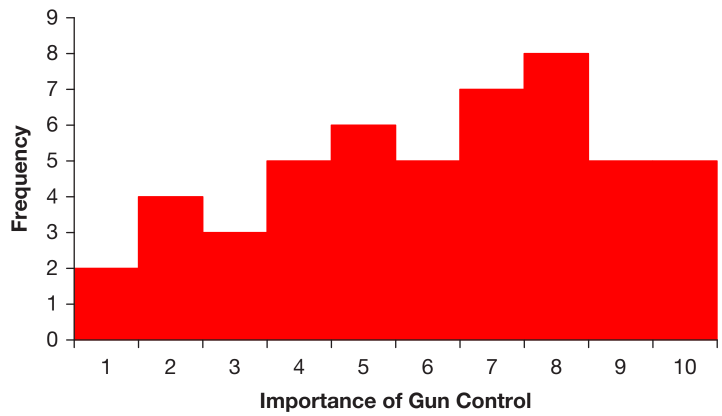


FIGURE 1.3 Histogram of Responses



central tendency. As you may have already guessed, the statistics that can be used to describe a variable depend on whether the variable is operationalized at the nominal, ordinal, or interval/ratio level.

VALIDITY AND RELIABILITY

As mentioned earlier, an old saying about statistics goes "garbage in, garbage out." There is a lot of truth to this statement, and it raises the issue that sound methodological decision making is the foundation for meaningful statistical analysis. In other words, if we are not careful in how we collect our data and measure our concepts, how can we have any faith in the statistics that come out of those data? Two terms are of particular importance: validity and reliability.

Validity refers to whether we are measuring what we think we are measuring. Does a variable actually reflect the concept that we think it does? **Reliability** refers to the likelihood that a particular measure yields consistent results over time. Is a questionnaire item worded in such a way that respondents interpret it in similar ways?

Validity: The degree to which a variable measures what we think it is measuring.

Reliability: The degree to which a measure yields consistent results.

Suppose a researcher wants to develop a questionnaire item to measure the class standing of a group of college students. When discussing class standing, most people probably think of an individual's relative position in the social structure on the basis of wealth, income, or power. Although *class standing* is not a difficult concept to grasp, it is a difficult concept to operationalize. Here are a couple questions that the researcher might ask:

What was your income last year (in dollars)?

What was your income last week (in dollars)?

Each of these questions does a pretty good job of measuring income, but problems arise with each of them. Are students who made higher amounts of income last year really of higher class standing than those who made lower amounts? Maybe, but it is also possible that some students might not need any income at all because they have a lot of money in the bank. Or perhaps they have very low income, or no income, because they receive a check from their parents every other week. In this sense, the questions are not valid because there is a good chance that we are not measuring what we think we are measuring.

Now consider the following questions:

Would you say that you live in a working-class, middle-class, or upper-class neighborhood?

Are you financially secure?

Each of these questions does a pretty good job of measuring respondents' subjective class identification, but they too have problems. For example, the first question forces respondents to choose from one of three attributes. Often people are reluctant to admit, or do not know, that they are more upper class than middle class. Americans like to fit in. Therefore, it is likely that a vast majority of respondents will answer "middle class." If we were to add one more attribute to the number of choices that respondents have, we might find that patterns emerge in the data that cannot be detected with only three attributes. Greater levels of precision, however, do not necessarily increase reliability.

The second question is not reliable because each respondent may read it in a completely different way. For example, one respondent might read the question after having just found out that she needs to buy $700 in books for the upcoming semester. Feelings of financial security may have disappeared during the course of an afternoon on hearing this news. In this sense, the measure could yield different results depending on the day-to-day finances of respondents instead of on their overall long-range financial positions.

When trying to measure difficult concepts like class standing, it is often best to use a variety of measures that can be analyzed independently or combined into a single overall (or composite) measure. For example, many sociologists use a combination of income, education, and occupation to determine respondents' overall socioeconomic status. It is important to remember that measures can be valid without being reliable; likewise, measures can be reliable without being valid. The goal is to strive for high levels of both validity and reliability to avoid the problem of garbage in, garbage out.

Individual Data

Every year, the National Opinion Research Center (NORC) at the University of Chicago conducts its annual General Social Survey (GSS). NORC has conducted this survey every year since 1972, and many of the questionnaire items have remained unchanged. This allows researchers to conduct *longitudinal* analyses (comparing changes in responses over time).

Sometimes the total sample of GSS respondents is more than 4,000. But not every respondent was asked every question. This means that responses from as few as 2,000 people are used to generalize to the entire population of the United States. Incredible as this may seem, the consistency of these statistics over time indicates that the data gathered are both valid and reliable. Needless to say, NORC researchers must be very diligent in their survey research methodology to ensure that the data are of high quality.

The GSS data are known as individual-level data because the variables represent characteristics of the individuals who were sampled (their sex, race, income level, political party affiliation, occupational prestige score, and attitudes toward hundreds of different social issues).

Tables 1.10, 1.11, and 1.12 show three examples of some of the GSS variables and how they are operationalized. The data in these tables represent all the responses from 1972 to 2006. As you can see in Table 1.11, the variable *sex* is operationalized as 1 = Male and 2 = Female. The numeric codes (1 and 2) are used in many statistical software programs and allow data entry to be done by entering numeric codes rather than typing out "Male" and "Female." You can see that since 1972, this questionnaire item has been administered to 51,020 respondents, and 22,439 of these respondents (44.0%) indicated that they are male. The remaining 28,581 indicated that they are female.

Tables 1.10, 1.11, and 1.12 are known as frequency tables. Table 1.11 shows data on respondents' highest degree, an ordinal variable, and Table 1.12 shows data on respondents' years of education, an interval/ratio variable. As Table 1.12 shows, interval/ratio variables do not have labels for their codes because the attributes are already in numeric form.

Frequency tables are discussed in greater detail in Chapter 2.

Ecological Data

The U.S. Bureau of the Census conducts a national census every 10 years. Census questionnaires come in both long and short forms, with most people answering on the short form. Although data are collected from individuals, no data in the census can be analyzed at the level of the individual. Instead, data are tallied by region of the country, state, county, minor civil division, census tract, block group, block, and other levels of analysis. In this way, census data allow researchers to compare characteristics of states, counties, cities, and so on without having any knowledge about specific individuals who provided the data. In fact, to protect the identity of people, many census variables are not available at the census tract, block group, or block level.

TABLE 1.10 Example of a Nominal Variable From the GSS

Sex	Respondent's Sex			
Text of This Question or Item				
23. Code respondent's sex				
% Valid	**% All**	***N***	**Value**	**Label**
44.0	44.0	22,439	1	Male
56.0	56.0	28,581	2	Female
100.0	100.0	51,020		Total
Properties				
Data type:			Numeric	
Missing data code:			0	
Record/column:			1/108	

Source: Data from the National Opinion Research Center, General Social Survey.

TABLE 1.11 Example of an Ordinal Variable From the GSS

Degree	Respondent's Highest Degree			
Text of This Question or Item				
19. If finished 9th–12th grade: Did you ever get a high school diploma or a GED certificate?				
% Valid	**% All**	***N***	**Value**	**Label**
23.2	23.1	11,777	0	Less than high school
51.7	51.6	26,307	1	High school
5.1	5.1	2,601	2	Junior college
13.6	13.6	6,918	3	Bachelor
6.4	6.4	3,253	4	Graduate
	0.1	29	8	Don't know
	0.3	135	9	No answer
100.0	100.0	51,020		Total
Properties				
Data type:		Numeric		
Missing data codes:		7, 8, 9		
Record/column:		1/104		

Source: Data from the National Opinion Research Center, General Social Survey.

TABLE 1.12 Example of an Interval/Ratio Variable From the GSS

Education	Highest Year of School Completed			
Text of This Question or Item				
15. What is the highest grade in elementary school or high school that you finished and got credit for?				
% Valid	**% All**	***N***	**Value**	**Label**
0.3	0.3	137	0	
0.1	0.1	38	1	
0.3	0.3	132	2	
0.4	0.4	223	3	
0.6	0.5	280	4	
0.7	0.7	371	5	
1.3	1.3	666	6	
1.6	1.6	811	7	
4.9	4.8	2,470	8	
3.5	3.5	1,765	9	
4.8	4.8	2,451	10	
6.0	6.0	3,065	11	
31.1	31.0	15,814	12	
8.3	8.3	4,235	13	
10.7	10.6	5,422	14	
4.3	4.3	2,211	15	
11.8	11.8	6,025	16	
2.9	2.9	1,482	17	
3.3	3.3	1,660	18	
1.3	1.3	648	19	
1.9	1.9	962	20	
	0.1	64	98	Don't know
	0.2	88	99	No answer
100.0	100.0	51,020		Total
Properties				
Data type:				Numeric
Missing data codes:				97, 98, 99
Record/columns:				1/96-97

Source: Data from the National Opinion Research Center, General Social Survey.

For example, suppose you and your family immigrate to the United States from the Dominican Republic and indicate on the census form that you are Dominican. It is likely, in most communities, that you are one of very few Dominican families. Therefore, if data on ethnicity were made available at the block or block group level, other people, using census data, would be able to learn more about your income level, your family makeup, and a host of other data that should be kept private. In other words, if data are made available at too "local" a level, you could be "outed" without your approval. Therefore, it is important that census data be made available in ways that maintain the anonymity of those who provided them.

Census data are collected and put into databases in interval/ratio form. For example, suppose we are interested in studying population in the state of Vermont. Communities could be defined as counties, towns and cities, zip codes, or block groups. Suppose we decide to analyze population by county and subsequently divide the state into its 13 counties. Table 1.13 shows each of the 13 counties, its total population, and its farm population from the 2010 U.S. Census. We can use these data to calculate the percent of each county's population who live on farms without revealing who those individuals are.

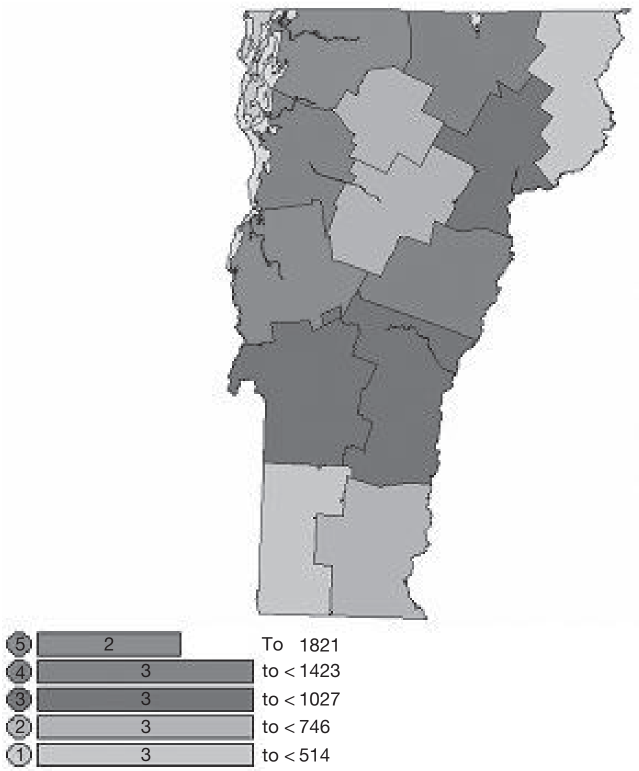
As Table 1.13 shows, Vermont's two biggest farm populations are located in Addison and Franklin counties. We do not know, however, where these counties are located or where they lie in relation to other counties with significant farm populations.

TABLE 1.13 Demographic Characteristics of Vermont Counties (N = 14)

County	Population	Farm Population	Percent Farm Population
Addison	35,974	1,429	4.0
Bennington	36,994	327	.9
Caledonia	29,702	824	2.8
Chittenden	146,571	1,027	.7
Essex	6,459	118	1.8
Franklin	45,417	1,821	4.0
Grand Isle	6,901	200	2.9
Lamoille	23,233	514	2.2
Orange	28,266	1,136	4.0
Orleans	26,277	1,031	3.9
Rutland	63,400	807	1.3
Washington	58,039	688	1.2
Windham	44,216	534	1.2
Windsor	57,418	746	1.3
Total	608,827	11,202	

Source: Data from the U.S Census Bureau, Census 2000.

FIGURE 1.4 Vermont Farm Population by County



Source: Data from the U.S Census Bureau, Census 2000.

It is possible, with a variety of software packages, to map census data to create visual representations that allow researchers to see geographic patterns in data that might not otherwise be noticed. For example, the map in Figure 1.4 shows that Vermont's farm population is heavily concentrated in two counties, and you can see that these two counties are located in the western part of the state in what is called the Champlain Valley.

When data are represented in multiple formats, such as tables, charts, and maps, it can be more enlightening, easier to interpret, and more effectively used.

EYE ON THE APPLIED

TAKING THE TRASH OUT OF STANDARDIZED TESTING

As is the case of all scientific inquiry, good social science research is dependent on high-quality data. This means that data should be both valid and reliable. If a measure of a concept is valid, we are really measuring what we believe we are measuring. Often this is not the case, and the consequences of invalid data can be summarized as garbage in, garbage out.

The No Child Left Behind Act gained widespread support across the nation and has the goal of ensuring that elementary, middle, and high school students achieve minimum levels of education as set by federal and state governments. Standardized tests are used to assess students' abilities. The percentage of students who pass these tests is then used as an indicator of schools' ability to educate their students. In this manner, standardized tests provide data that are used to assess individual students as well as entire schools or even school districts.

Standardized testing is believed to assess the cognitive abilities of students and, therefore, acts as an indicator of how good a job schools are doing; however, it might not do that. For example, in many urban high schools, English is not the first language for many students. This can generate lower test scores for non-English-speaking students. Suppose a history course focuses on the transition from agricultural to industrial economies. The students understand the ideas and can write about them, but on the standardized test the term "agrarian" is more likely to be misinterpreted by students for whom English is not their first language. In this way, the standardized test is biased and not valid because it measures English proficiency, not knowledge of history. Therefore, it is debatable whether the schools are failing students or whether the standardized tests are failing the schools.

A second and more likely problem with standardized testing is the assumption that schools with higher percentages of students who pass the exams are better schools. Is a high school in which 87% of the students pass a standardized test a better school than one in which 77% of the students pass? Are the students really learning more? Perhaps they are just learning different content, some of which is assessed on standardized tests and some of which is not.

One trend that most educators agree on is that if you teach only the material that will appear on a test, more of the students will pass that test. Is the school in which 87% of the students pass teaching only the material that will be on the test? If so, then the outcome of standardized testing is to reduce overall learning to a narrowly defined curriculum of items that appear on tests.

In the world of education reform and standardized testing, it is useful not only to understand how to interpret statistics but also to understand the social conditions (political and otherwise) in which those statistics were generated.

When working with data representing individuals, it is important not to fall victim to the individualistic fallacy. This is a mistake that occurs when researchers infer characteristics of members of a group based on information they obtained from one person in that group. It can be thought of as overgeneralizing.

Consider the following example. You go to visit a friend in Boston over spring break. While staying at this friend's house, you overhear a number of conversations and complaints regarding problems with high taxes. When you return home, you mention to some other friends that Bostonians are in support of lower taxes. The problem is that you have taken a small (unscientific) sample of Bostonians who are all part of the same group of acquaintances and used their opinions to generalize to the whole city of Boston.

The individualistic fallacy can be thought of as generalizing from the individual (or small group) to larger groups.

Another term to be considered is called the ecological fallacy. The ecological fallacy is a type of error in which characteristics of an area or a region are believed to be the characteristics of the people in that region. Consider the following example. The state of Oklahoma has one of the largest Native American populations (as a percentage of the total population) of all the states. It is also a state that ranks very high in per capita alcohol consumption. Therefore, Native Americans are heavy drinkers.

It is important, however, to consider other possibilities. Oklahoma is home to a significant number of Indian reservations. Often these reservations are home to casinos where a significant amount of alcohol consumption takes place by those who gamble. Therefore, it might not be the Native Americans who are consuming all the alcohol. As you can see, the ecological fallacy has the potential to foster and perpetuate stereotypes.

In sum, the ecological fallacy is a mistake that is made when we impose characteristics of a group on individuals in that group.

Individualistic fallacy: A type of error that occurs when the characteristics of an individual are imposed on all the members of a group to which that individual belongs.

Ecological fallacy: A type of error that results from drawing conclusions about individuals from characteristics of a group.

Example of Individual-Level Data: Studiousness

We begin with the concept of *studiousness*. This can refer to many different ideas—attending class regularly, studying outside of class time, and doing all the assigned readings. Suppose that we define studiousness as the number of hours a person spends studying outside of class each week. We can measure this concept on a questionnaire in many different ways.

Consider the following:

Nominal: Do you study in the library? (Yes, No)

Ordinal: How often do you study in the library? (Never, Sometimes, Often)

Interval/ratio: How many hours do you spend studying in the library each week?

Our conceptual definition of studiousness is the effort that one puts into being a student. Our operational definition of studiousness is done in three different ways. Each has its own advantages and limitations. It is always possible that our operational definitions have little to do with the actual concept with which we began. When our operational definition fails to measure the concept with which we began, we say the variable is lacking *validity*.

For example, if we asked our respondents how many hours they went to the library each week, we could have an invalid measure. It is possible that some students go to the library only to take naps. In this case, a significant number of hours in the library would not indicate greater levels of studiousness. Or it may be that some students indicate they never go to the library. Does this mean they are not studious? It may be that they have a home office or other place where they do their studying.

If this is the case, it means that our questionnaire measures only part of the concept we intend it to measure. It may be that some students do not use the library at school because they have a better place to study. Or it may mean that they study in other places because they are not afforded the opportunity to study in the library. In either case, we cannot safely conclude that a student who does not study in the library very often is not studious. In this sense, our indicator lacks what is called *content validity* in that it measures only part of what we want it to measure.

Ultimately, social scientists can measure anything, but only with varying degrees of validity and reliability. Validity refers to the question "Are we measuring what we think we are measuring?" Reliability refers to the question "Can we expect consistent results if our measure is repeated?" In other words, do all our respondents understand the question in the same way?

Validity refers to the ability of a measure to accurately reflect the concept it is intended to measure. Reliability refers to the ability of a measure to collect similar data each time it is applied.

1. The number of hours you spend studying each day (0, 1, 2, 3, 4, 5, . . .). Ratio
2. How often you would say you study (None, Some, A lot). Ordinal
3. Your favorite subject in school. Nominal
4. Your frequency of skipping classes (Never, Sometimes, Often). Ordinal
5. The number of classes you skipped last semester (0, 1, 2, 3, 4, . . .). Ratio
6. The number of study group meetings you had last semester (0–1, 2–3, 4–5, 6+).

Don't be fooled by Item 6. Grouped data are ordinal variables.

Example of Ecological Data: Toxic Hazards and Other Locally Unwanted Land Uses

Locally unwanted land uses (often referred to as LULUs) can take many forms, ranging from toxic waste sites to wind farms. Toxic waste sites in particular pose a wide range of threats to both environmental and human health and include Superfund sites, state-level hazardous sites, industrial emissions, landfills, incinerators, waste-to-energy plants, tire piles, and trash transfer stations, among others.

A colleague of mine, Daniel Faber from Northeastern University in Boston, and I spent a number of years developing variables to assess the relative contamination of one community to the next. We found that by using only one or two indicators of ecological hazards, say state-level hazardous sites and landfills, our indicator suffered from a lack of content validity. In other words, we were measuring only a portion of the total hazards and could not compare the relative contamination levels in one town with those in the next town.

Ultimately, we came up with a composite measure that included 17 different types of ecological hazards. Each type of hazard was awarded a certain number of "points,"

and when the points were tallied for each community, they represented what we call each community's ecological hazards points (or EHPs). EHP is a ratio variable that in 2005 ranged from 0 in some small remote towns in Massachusetts to about 3,500 in the city of Boston.

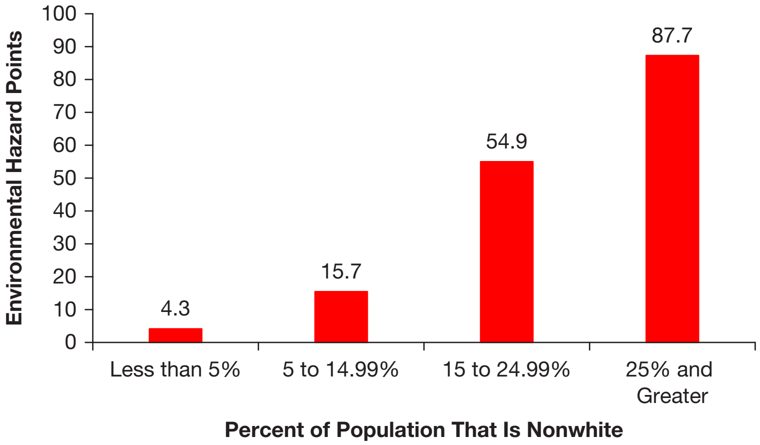
Because each community is a different size, we then divided the number of EHPs by the number of square miles of land in each community to get EHPs/square mile. This allowed us to compare the relative risks that each community faced.

After developing this variable, we were able to test whether lower-income communities and those with significant non-white populations were most likely to have high ecological hazard scores. Not surprisingly, they were. To arrive at this conclusion, we divided all the communities into four groups based on the percentage of the total population that was non-white. In other words, we began with a ratio variable and recoded it into an ordinal variable.

1. Percentage of population that is non-white (0, 1, 2, 3, 4, . . . , 100). Ratio
2. Percentage of population that is non-white (0–4.9%, 5–14.9%, 15–24.9%, 25% and higher). Ordinal
3. Number of EHPs/square mile in community (0, 1, 2, 3, 4, . . . , 127). Ratio
4. Number of EHPs/square mile in community (0–5, 6–10, 11–15, 16 or more). Ordinal

The chart in Figure 1.5 shows the relationship between EHPs per square mile and the percentage of non-white population. In this chart, EHP is operationalized as an

FIGURE 1.5 Environmental Hazard Points per Square Mile by Race

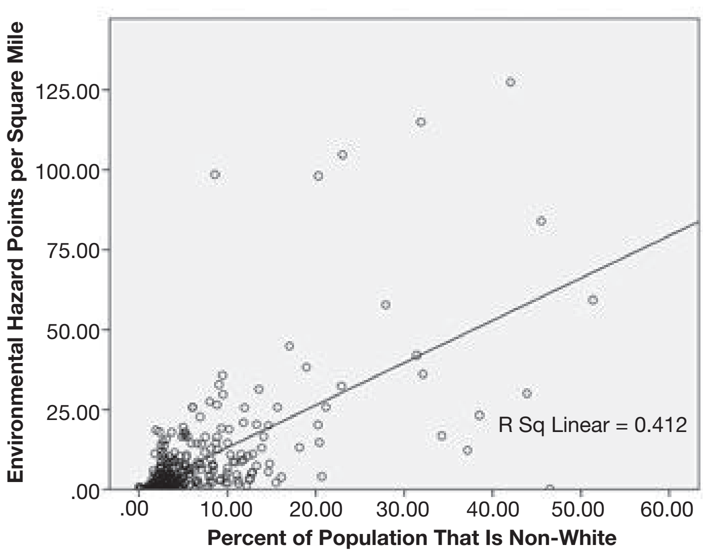


Source: Data from the U.S Census Bureau, Census 2000 and MA Department of Environmental Protection.

interval/ratio variable and race is operationalized as an ordinal variable. As you can see, the number of environmental hazard points increases as the percentage of the population that is non-white increases.

The chart in Figure 1.6 shows the relationship between EHPs per square mile and the percentage of non-white population (variables operationalized at the ratio level). A "best fit" line has been added to the chart to more clearly show the trend in the data. As in Figure 1.5, the trend shows a positive association between the two variables—as the percentage of the non-white population increases, so does the intensity of ecological hazards.

FIGURE 1.6 Environmental Hazard Points per Square Mile by Race



CHAPTER SUMMARY

This chapter focused on three main ideas: concepts, variables, and measurement. Concepts are ideas that we have about the world around us, variables are characteristics that vary from case to case, and measurement refers to the ways that we choose to assess the characteristics that vary from case to case. Because concepts are ideas based on what we know, we should expect them to change over time. As Kuhn argued in his book *The Structure of Scientific Revolutions* (1962), ideas about the world often change rapidly. Consequently, the ways that we conceptualize and operationalize variables also change over time. Measurement can be done at the nominal, ordinal, and interval/ratio levels. In all three types, the attributes of variables must be collectively exhaustive and mutually exclusive. Two types of data that social scientists work with are individual data and ecological data. While individual data describe characteristics of individuals, ecological data describe characteristics of groups or regions.

CHAPTER EXERCISES

1. Suppose we conceptualize academic achievement to mean how well a person does in school. Operationalize this concept in two ways.
2. Suppose you want to operationalize racism at the individual level (the degree of racist opinions a person holds). Operationalize this concept in two ways.
3. Come up with a way to operationalize proficiency in Spanish.
4. In your own words, explain what is meant by the term *mutually exclusive*.
5. In your own words, explain what is meant by the term *collectively exhaustive*.
6. Explain the difference between conceptualization and operationalization.
7. What is the problem with the variable in Table 1.14?

TABLE 1.14

The Number of Books You Read Last Summer
0–2 books
2–4 books
4–6 books
6 or more books

8. What is the problem with the variable in Table 1.15?

TABLE 1.15

The Number of Books You Read Last Summer
1–2 books
3–5 books
6 or more books