2 EDITION

FUNDAMENTAL STATISTICS for the Social and Behavioral Sciences

Howard T. Tokunaga

Fundamental Statistics for the Social and Behavioral Sciences

Second Edition

To my kids, Meagan and Will, and my parents,
Katsumi and Grayce Tokunaga.

Fundamental Statistics for the Social and Behavioral Sciences

Second Edition

Howard T. Tokunaga
San Jose State University

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PREFACE TO THE SECOND EDITION

Perhaps the most appropriate way to introduce the second edition of this book is to thank the instructors who adopted the first edition and were kind enough to send me their thoughts and suggestions, as well as the reviewers of the first edition who were amazingly insightful and thoughtful in their comments and observations. It is my sincere hope that they see the incorporation of their input in this edition.

The primary changes made to the book involve both formatting and content. In terms of formatting, the readability of the book was hopefully enhanced through such things as reorganizing the chapter outlines at the start of each chapter, reducing the size of figures, and more clearly distinguishing the learning checks and end-of-chapter summaries. In terms of content, in addition to making minor editing and grammatical changes throughout the book, the following changes were made to selected chapters:

> Chapter 1 (Introduction to Statistics) and Chapter 2 (Examining Data: Tables and Figures): The published research studies used to illustrate the concepts discussed in these two chapters (research hypotheses, independent and dependent variables, sampling, levels of measurement, experimental vs. nonexperimental research methods, different types of distributions [unimodal, bimodal, multimodal, skewed]) have been updated to highlight current research trends on topics relevant to students' lives.
>
> Chapter 4 (Measures of Variability): "'Eyeball Estimating' the Mean and Standard Deviation" has been added to emphasize the value in having students visually estimate the mean and standard deviation for a set of data in order to confirm the correctness of their mathematical calculations. Also, the "Measures of Variability for Nominal Variables" section discusses a statistic (the index of qualitative variation) that may be used to measure the variability of categorical variables.
>
> Chapter 6 (Probability and Introduction to Hypothesis Testing): This chapter provides a greater elaboration of the logic used to make the decision whether to reject the null hypothesis, as well as the implication of this decision (reject vs. not reject) for a stated research hypothesis.
>
> Chapter 8 (Estimating the Mean of a Population): The main research example, which involves data from an actual national salary survey, has been updated with 2017 salary data in order to provide students information about current occupational information.
>
> Chapter 13 (Correlation and Linear Regression) from the first edition has been divided into two chapters. The new Chapter 13 (Correlation) covers the concept of correlation and correlational statistics (Pearson and Spearman rank-order correlation). Chapter 14 (Linear Regression and Multiple Correlation) discusses linear regression and also provides an in-depth introduction to multiple correlation and regression, using an example with two predictor variables to demonstrate the calculation, interpretation, and application of the multiple correlation coefficient and the multiple regression equation. Also, a new research example is used to illustrate correlation and linear regression; this example, which focuses on children's eating behaviors, addresses a topic students can relate to in their own lives.

Ultimately, the main goals of this second edition were to update the research examples used to illustrate statistical procedures and respond to users' and reviewers' reactions to the first edition. As with the first edition, it is our hope that this book will help students understand the use of statistics to answer questions and test ideas and to appreciate how research studies are conceived, conducted, and communicated. Any and all questions, concerns, suggestions, and complaints you have about the book are most welcome, and can be sent to me at howard.tokunaga@sjsu.edu.

PREFACE TO THE FIRST EDITION

It may surprise students to learn they have something in common with writers of books such as this one: When you get close to finishing a writing assignment, you get a bit tired and a bit lazy. The first attempt at this preface was written shortly after final drafts of chapters were sent to my editor at SAGE, Vicki Knight. After reading it, she said, "It's not bad, but it reads like the 'typical' Preface. I think it would be useful for the reader to have a sense of *why* you wrote this book and *why* you wrote it the way you did."

In responding to my editor's plea for self-analysis, I found that this book's journey began in college. When I entered college, I thought my path would take me to law school; however, taking an Intro to Psych class my freshman year made me realize I enjoy the challenge of trying to understand the human mind. The school I attended, UC Santa Cruz, was a fairly unconventional university, but somehow in the midst of a sea of humanistic psychologists, I became attracted to the empirical and methodological aspects of psychology. This was a result of taking classes with instructors such as David Harrington and Dane Archer, who showed me that statistics could appeal to students if taught using a gentle, guiding approach that addresses questions relevant to students' lives. After graduating from college, I was able to get a job as a research assistant for a human resource consulting firm. Despite my lack of work experience, I was hired primarily as a result of having taken statistics and research methods courses, which taught me that learning statistics has benefits both inside and outside of the classroom.

Several years later, I started grad school at UC Berkeley, where two events critical to this book took place. First, serving as a teaching assistant, I found I really enjoyed helping students, particularly in statistics and research methods classes that were often viewed with fear and suspicion. Second, I took graduate classes from Geoff Keppel, who had developed his own unique method and system for analyzing experimental research designs. His lectures and books were instrumental in showing me that statistics can be taught in a systematic way that highlights similarities rather than differences between different research situations. Geoff managed to transform something as daunting sounding as a "3 × 2 × 4 research design" into the mathematical equivalent of playing with wooden toy alphabet blocks labeled "A," "B," and "C." For a long time, I thought my gratitude to Geoff was an isolated occurrence. However, the appreciation others have for his approach to teaching statistics was made apparent to me several years later when I watched him receive an American Psychological Association (APA) Lifetime Achievement award.

After leaving Cal, I took on a teaching position at San Jose State, where my teaching responsibilities included an introductory statistics course aimed at students with a wide range of background, ability, and motivation. As I needed to select a textbook to use in this course, for the first time I looked carefully at the wide range of offerings. What I found striking (and still find striking) was that the majority of books focused on providing formulas and very small sets of data designed to demonstrate how to correctly calculate the correct numbers from these formulas. Little emphasis, however, was given to what these numbers meant or implied. Given my own experiences learning statistics, I thought a book was needed that discusses statistics in a thematic manner, focusing on how they are used to answer questions and test ideas within the larger research process.

The primary purpose of this book is to not just teach students how to calculate statistics but how to interpret the results of statistical analyses in light of a study's research hypothesis and to communicate one's results and interpretations to a broader audience. Hopefully, this book will not only help students understand the purpose and use of statistics but also give them a greater understanding of how research studies are conceived, conducted, and communicated.

The 14 chapters of this book may be placed into three general categories. The first four chapters are designed to introduce students to the research process and how data that have been collected may be organized, presented, and summarized. Chapters 5 through 10 discuss the process of conducting statistical analyses to test research questions and hypotheses, as well as issues and controversies regarding this process. The final four chapters of this book, Chapters 11 to 14, discuss different statistical procedures used in research situations that vary in the number of independent variables in the study as well as how the independent and dependent variables have been measured.

A FEW TIPS FOR STUDENTS

To you, the college student about to read this book as part of taking a statistics course: "Welcome!" and "Great job!" I welcome you because you're about to embark on a semester-long journey that I hope will enhance your skills and widen your perspective; I congratulate you because it's a journey not everyone is willing to take.

At the present moment, I know my encouragement and appreciation may be of little comfort to you as you might be somewhat anxious about having to learn statistics. Some of you might be anxious about having to learn statistical concepts and formulas; some of you might be anxious because the research process seems pretty complicated. Talking with students who have taken my courses over the years has helped me assemble the following advice:

Master the material presented in the early chapters

Chapters 1 through 6 discuss how research is often conducted, how data are summarized and described, and the process by which researchers conduct statistical analyses to test their ideas. It is absolutely critical for you to have a firm understanding of these chapters as they lay the groundwork for later chapters that discuss a variety of statistical procedures used by researchers to test hypotheses.

What does it mean to master this material? First, *read the chapters both before and after they're discussed in class*. By reading the chapters beforehand, you'll be able to identify anything that's unclear to you and have your questions addressed by your instructor. Rereading the chapters after they're discussed in class will help confirm your understanding of the material. Next, *be able to define and explain key concepts presented in these chapters*. These concepts are highlighted in bold-faced type, and it is important to learn them when they're first introduced because they'll appear throughout the remainder of the book. Next, *do the learning checks within the chapters and the exercises at the end of the chapters*. The learning checks include both exercises and review questions you can ask yourself to assess your understanding of the material. Most important, *do not miss class during the early part of the semester!* It's been my experience that students who miss critical lectures at the beginning of the term often have difficulty keeping up as the semester continues.

Review high school algebra

If you read newspapers or watch television, you might conclude that the most complicated data analysis people can comprehend is a pie chart. As frustrating as this is to researchers and statistics instructors, they understand that statistics can be confusing. If you happen to move beyond the introductory statistics course for which you are reading this book, you'll find that statistical procedures are often conducted using computers and statistical software rather than hand calculations. Consequently, some statistics textbooks no longer include mathematical formulas but instead have students conduct analyses using statistical software or Microsoft Excel. However, this book has chosen a different approach for two main reasons. First, I believe that to comprehend the results of data analysis, one must understand the underlying foundation of statistical procedures. Learning statistics via computer software can lead to a "brain-dead" approach in which students are at the mercy (rather than control) of their computers. I refer to this as the "I'm only as smart as my printout" method of learning statistics, also known as "Because this is what my computer told me."

Second, my steadfast and somewhat stubborn adherence to an approach emphasizing mathematical formulas and calculations is based on a simple reason: The statistics in this book are not hard to calculate! To assess whether you're adequately prepared to read this book, take the following test:

(1) Do you know how to add, subtract, multiply, and divide?

(2) Do you know how to calculate the "square" or "square root" of a number?

(3) Do you understand the "order of operations" and how to use parentheses within mathematical calculations?

If your answers to these questions are yes, congratulations! You possess the ability to conduct every mathematical calculation in this book. None of the formulas in this book requires knowledge of geometry, trigonometry, or calculus. However, if you're unsure of your mathematical ability, you may want to review your high school algebra. At the end of this book is an appendix that includes the mathematical concepts and operations needed to conduct the statistical analyses in this book. I highly recommend you read this appendix to review and assess your mathematical skills.

Learn to use a statistical calculator

Although learning the statistics in this book doesn't require the use of computers or software, you will need a hand calculator. Calculators with statistical capabilities are typically identified as statistical or scientific calculators. Although there's a wide selection of brands and models, one simple criterion to use in selecting a calculator is price. The statistical calculators most appropriate for this book cost somewhere in the $10 to $15 range at the time of this writing. I do *not* recommend you use or purchase a more expensive calculator! I prefer these simpler calculators because I've found students are able to conduct the calculations in this book more quickly and with fewer errors. I also recommend you purchase a calculator similar to the one your instructor uses as he or she will be more familiar with its features and idiosyncrasies.

In selecting a calculator, look closely at the keyboard; you'll need a calculator whose keys have labels such as "$\bar{X}$," "σ," and "ΣX" (Chapters 3 and 4 discuss what these symbols represent). When you go calculator shopping, you'll find calculators that have keys with labels such as "ΣY" and "XY." Although calculators with these "Y" symbols are only slightly more expensive than calculators with just the "X" symbols, I do *not* recommend their purchase because these features are not needed to perform the calculations in this book. In fact, I've found students with "Y" calculators have a more difficult time performing simpler calculations.

Ask questions

Conducting research is the process of asking and answering questions. Accordingly, throughout this book, issues are often framed in the form of questions, which I hope encourages you to ask questions as well. The first person you should direct any questions to is yourself. As you work your way through the chapters, get into the habit of asking yourself, "What does this mean?" A good test of your level of comprehension is whether you can explain the material to yourself in a meaningful way.

Also, be sure to work with your instructor to confirm your level of understanding and clarify unanswered questions. Instructors often say to students, "The only 'bad' question is the one you don't ask." Don't be hesitant about asking questions in class. Instructors will tell you they use one student's question to assess an entire class' level of understanding. This is what I call the "pencil test"—when one student asks a question, I look to see how many other pencils get raised, which reflects the number of students who had the same question and are ready to write down the response. Asking questions enhances the learning experience for yourself, your classmates, and your instructor.

Form a study group

No matter how much I encourage students to ask questions in class, it seems they hesitate for fear of drawing attention to themselves. As a result, I turn to another well-traveled saying: "Misery loves company." Forming a study group to meet with other students on a regular basis will help you keep up with reading assignments, confirm your comprehension of the material, clarify any confusion you have, prepare for exams, and receive an invaluable source of social support. I do suggest that your group contain at least one person who will raise the group's questions and concerns to the instructor in class or office hours.

Practice, practice, practice

The best way to learn the topics covered by this book is to obtain as much practice as possible. Throughout the chapters are examples in which the calculations have been worked out for you; in the middle and end of each chapter are a number of exercises. The answers to some of the exercises are provided at the back of this book, and your instructor has access to the answers to the other exercises. Do the end-of-chapter exercises even if your instructor does not assign them as homework in order to identify any recurring mistakes you make. We find that the vast majority of errors students make are simple computational errors, committed when students do the calculations too quickly.

WELCOME!

GREAT JOB!

ACKNOWLEDGMENTS

This book has traveled a long journey, with many people playing both transient and persevering roles in its development. First and foremost, I'd like to thank my kids, Meagan and Will, for providing me perspective and inspiration amid all of the twists and turns we faced while this book was being written. I'm so very blessed to have you as my "burden." Away from home, I'm grateful to my graduate students at San Jose State—working on this book has given me much empathy for their thesis-related travails. However, they should be aware that the completion of this book ends the unspoken agreement that I not ask, "So how's your thesis?" if they don't ask, "So how's your book?" A number of friends have provided most welcome relief after long days staring at a computer screen, with particular thanks going to Ellie, Eileen, Susan, Bonnie, Ann, Lisa, and Terry. I would like to thank Charles Linsmeier and David Shirley for their many helpful comments and advice on earlier versions of this book, and Julie West for her help in developing chapter exercises.

I would like to express my appreciation to everyone at SAGE who has played a role in shepherding this book to completion. First and foremost, I must express my gratitude to my editor, Vicki Knight. It has been a joy and an honor to work with someone with such a truly exceptional combination of experience, knowledge, perspective, and humor. In production I was fortunate enough to work with others on the SAGE team who made the process a pleasure: Yvonne McDuffee, Editorial Assistant; Katie Guarino, Assistant Editor; Nicole Elliott, Executive Marketing Manager; Candice Harman, Cover Designer; and the copyeditor, Gillian Dickens. Furthermore, I am grateful to the reviewers, who took the time to read the chapters, raise questions, and provide constructive comments and suggestions to assist me in clarifying and strengthening the manuscript. Reviewers for second edition:

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1

INTRODUCTION TO STATISTICS

CHAPTER OUTLINE

In introducing this book to you, we assume you're a college student taking what is perhaps your first course in statistics to fulfill a requirement for your major or a general education requirement. If so, you may be asking yourself two questions:

- What is statistics?
- Why learn statistics?

The ultimate goal of this book is to help you begin to answer these two questions.

1.1 WHAT IS STATISTICS?

Whether or not you are aware of it, you encounter a variety of "statistics" in your day-to-day activities: the typical cost of going to college, the yearly income of the average college graduate, the average price of a home, and so on. So what exactly is "statistics"? The Merriam-Webster dictionary defines **statistics** as a branch of mathematics dealing with the collection, analysis, interpretation, and presentation of masses of numerical data. When people think about statistics, they often focus on only the "analysis" aspect of the above definition—that is to say, they focus on numbers that result from analyzing data. However, statistics not only is concerned about how data are analyzed but also recognizes the importance of understanding how data are collected and how the results of statistical analyses are interpreted and communicated. The main purpose of this book is to introduce, describe, and illustrate the role of statistics within the larger research process.

1.2 WHY LEARN STATISTICS?

We believe there are a variety of reasons why you should learn statistics. First, not only do you currently encounter statistics in your daily activities, but throughout your life you have been and will continue to be affected by the results of research and statistical analyses. Which college or graduate school you attend is based in part on test scores developed by researchers. You may have to take a personality or intelligence test to get a job. The choices of drugs and medicines available to you are based on medical research and statistical analyses. If you have children, their education may be affected by their scores on standardized tests. Learning about statistics will help you become a more informed and aware consumer of research and statistical analyses that affect many aspects of your life.

A second reason for learning statistics is that you may be required to interpret the results of statistical analyses. Many college courses require students to read academic research journal articles. Evaluating published research is complicated by the fact that different people studying the same topic may come up with diverse or even opposing conclusions. Understanding statistics and their role in the research process will help you decide whether conclusions drawn in research articles are appropriate and justified.

Another reason for learning statistics is that it will be of use to you in your own research. College courses sometimes have students design and conduct mini-research studies; undergraduate majors might require or encourage students to do senior honors theses; graduate programs often require masters' theses and doctoral dissertations. Learning to collect and analyze data will help you address your own questions in an objective, systematic manner.

A final reason for learning statistics is that it may help you in your future career. The website Careercast.com conducts an annual survey in which they evaluate jobs on four dimensions: environmental factors, income, employment outlook, and stress. In 2017, the number one rated job was "statistician." They noted, "A statistician's skill set can be used to break down and analyze large quantities of data. The demand for these skills spans a variety of industries, including marketing, banking, government, sports, retail, and even healthcare."

It is generally a good idea for students to maintain a healthy level of curiosity or even skepticism in regards to their education. However, we find that when it comes to learning statistics, students' frame of mind may be characterized as one of fear or anxiety. Although we understand these feelings, we hope the benefits of learning statistics will become clear to you and help overcome any concerns you have.

1.3 INTRODUCTION TO THE STAGES OF THE RESEARCH PROCESS

Much of scientific research involves asking questions. Throughout this book, we'll examine a broad range of questions regarding human attitudes and behavior that contemporary researchers have asked and attempted to answer. Below are research questions we'll address in this chapter to introduce the stages of the research process:

- Is college students' performance on tests more influenced by their learning strategies (*how* they learn) or their motivation (*why* they learn)?
- How do parents' feeding practices affect whether their children will eat new foods?

- Does coercive interrogation of eyewitnesses affect their accusations of crime suspects?
- Are there gender differences in terms of who contributes to Wikipedia?

How might you try to answer questions such as these? You could base your answers on your personal beliefs, or you could adopt the answers given to you by others. But rather than relying on subjective beliefs and feelings, researchers test their ideas using science and the scientific method. The **scientific method** is a method of investigation that uses the objective and systematic collection and analysis of empirical data to test theories and hypotheses.

At its simplest, this book will portray the scientific method as consisting of five main steps or phases:

- developing a research hypothesis to be tested,
- collecting data,
- analyzing the data,
- drawing a conclusion regarding the research hypothesis, and
- communicating the findings of the study.

Accomplishing each of these five steps requires completing a number of tasks, as shown in Figure 1.1. Because this sequence of steps will serve as the model for the wide assortment of research studies we'll review and discuss throughout this book, each step is briefly introduced below. It's important to understand that the research process depicted in Figure 1.1 represents an ideal way of doing research. The "real" way, as you may discover in your own efforts or from speaking with researchers, is often anything but a smooth ride but rather is filled with false starts, dead ends, and wrong turns.

Developing a Research Hypothesis to Be Tested

The initial stage—and the first step—of the research process is to develop a research hypothesis to be tested. A **research hypothesis** may be defined as a statement regarding an expected or predicted relationship between variables. A **variable** is a property or characteristic of an object, event, or person that can take on different values. One example of a variable is "U.S. state," a variable with 50 possible values (Alabama, Arkansas, etc.).

Research hypotheses are usually developed through the completion of several tasks:

- identifying a question or issue to be examined,
- reviewing and evaluating relevant theories and research, and
- stating a research hypothesis.

Each of these three tasks is described below.

Identifying a Question or Issue to Be Examined

Most research starts with a question posed by the researcher that often comes from the researcher's own ideas and daily observations. Although this may not seem terribly scientific, there is an advantage in using one's own experience as a starting point: People are generally much more motivated to explore issues that concern them personally. In teaching statistics, we advise students developing their own research projects to study something of interest to them. Conducting research can be tedious, difficult, and frustrating. At various points, you may

FIGURE 1.1 ● STEPS IN THE RESEARCH PROCESS WITHIN THE SCIENTIFIC METHOD

Develop a research hypothesis to be tested

Identify a question or issue of interest
Review and evaluate relevant theory and research
State a research hypothesis

Collect data

Draw a sample from a population
Determine how the variables will be measured
Select a method to collect the data

Analyze the data

Calculate descriptive statistics
Calculate inferential statistics

Draw a conclusion regarding the research hypothesis

Communicate the findings of the study

ask yourself, "Why am I doing this?" Being able to provide a satisfactory answer to this question will help you overcome obstacles you encounter along the way.

Reviewing and Evaluating Relevant Theories and Research

Beyond the researcher's own curiosity, research questions often arise from an examination of the theories, ideas, and research of others. A **theory** is a set of propositions used to describe or explain a phenomenon. The purpose of a theory is to summarize and explain specific facts using a logically consistent framework. Placing a question within a theoretical framework provides guidance and structure to research.

Reviewing and evaluating existing theories and research helps the researcher decide whether it is worth the time and energy required to conduct the study. By seeing what others have done, the researcher may decide that a particular idea has already been investigated and there is no reason to duplicate earlier efforts. However, the researcher may conclude that the current way of thinking is incomplete or mistaken. By doing this review, researchers are able to ensure that the studies they undertake add to and improve upon an existing body of knowledge.

Stating a Research Hypothesis: Independent and Dependent Variables

Understanding and evaluating an existing literature not only helps articulate a question of interest but also may lead to a predicted answer to that question. Within the scientific method, this answer is stated as a research hypothesis, defined earlier as a statement regarding an expected or predicted relationship between variables. Table 1.1 lists the research questions and research hypotheses for the studies listed at the beginning of this section. For example, the first research hypothesis states that "students who are taught effective learning skills will perform better on tests than students offered incentives to do well."

One characteristic of research hypotheses such as those listed in Table 1.1 is that they identify the variables that are the focus of their research studies. As mentioned earlier, a variable is a property or characteristic with different values. Variables can be classified in several ways. In specifying a research hypothesis, researchers often speak in terms of "independent" and "dependent" variables. An **independent variable** may be defined as a variable manipulated or controlled by the researcher. A **dependent variable**, on the other hand, is a variable measured by the researcher that is expected to change or vary as a function of the independent variable. The independent variable is seen as the "cause" or "treatment," whereas the dependent variable is the "effect" or "outcome." Researchers are interested in examining the effect of the independent variable on the dependent variable.

Consider the first research hypothesis provided in Table 1.1: "Students who are taught effective learning skills will perform better on tests than students offered incentives to do well." Here the independent variable is the instructional method by which students are taught, which consists of two values: learning skills and incentives. The dependent variable is the test performance that will be measured during the research. In this study, the effect of the independent variable on the dependent variable is that differences in students' test performance (the dependent variable) may "depend" upon which instructional method (learning skills or incentives) a student receives. Table 1.2 lists the independent and dependent variables for each of the research hypotheses in Table 1.1.

In addition to identifying variables, a second characteristic of research hypotheses is that they specify the nature and direction of the relationship between variables. For example, the first research hypothesis in Table 1.1 states that "students who are taught effective learning skills will perform *better* on tests." The word *better* indicates the nature and direction of the relationship between the independent variable (instructional method) and the dependent variable (test performance). The direction of the relationship would not have been stated if the hypothesis had included the less specific phrase "will perform *differently* on tests," which simply indicates that the two groups are not expected to be the same. Table 1.3 provides directional and nondirectional research hypotheses for the research studies from Table 1.1.

The ability to form a directional research hypothesis is dependent on the state of the existing literature on the question of interest. If little or perhaps conflicting research has been conducted, researchers may not be able to form a directional hypothesis before they begin their research. One study, for example, examined the relationship between exercise deprivation (not allowing people to exercise) and tension, depression, and anger

TABLE 1.1 ⬢ EXAMPLES OF RESEARCH QUESTIONS AND HYPOTHESES

Research Question	Research Hypothesis
Is college students' performance on tests more influenced by their motivation (*why* they learn) or their learning strategies (*how* they learn)?	Students who are taught effective learning skills will perform better on tests than students offered incentives to do well.
How do parents' feeding practices affect whether their children will eat new foods?	Greater use of forceful feeding practices leads to greater food refusals.
Does coercive interrogation of eyewitnesses affect their accusations of crime suspects?	Coercive interrogation increases eyewitnesses' false accusations.
Are there gender differences in terms of who contributes to Wikipedia?	Women are less confident in contributing to Wikipedia than are men.

TABLE 1.2 ● RESEARCH HYPOTHESES AND THEIR INDEPENDENT AND DEPENDENT VARIABLES

Research Hypothesis	Independent Variable	Dependent Variable
Students who are taught effective learning skills will perform better on tests than students offered incentives to do well.	Instructional method	Test performance
Greater use of forceful feeding practices leads to greater food refusals.	Use of forceful feeding practices	Frequency of food refusals
Coercive interrogation increases eyewitnesses' false accusations.	Type of interrogation	Making a false accusation
Women are less confident in contributing to Wikipedia than are men.	Biological sex	Level of confidence

(Mondin et al., 1996). The researchers for the study reported, "We did not have a directional hypothesis, and when participants asked what we expected to find in this study, we replied: 'We really are not sure since the results of earlier work on exercise deprivation are mixed'" (p. 1200).

Collecting Data

Once a research hypothesis has been formulated, researchers are ready to proceed to the second stage in the research process: collecting data relevant to this hypothesis. This step is seen as being composed of three tasks:

- drawing a sample from a population,
- determining how the variables will be measured, and
- selecting a method by which to collect the data.

Drawing a Sample From a Population

The first step in collecting data is to identify the group of participants to which the research hypothesis applies. The group to which the results of a study may be applied or generalized is called a population. A **population** is the total number of possible units or elements that could potentially be included in a study. For

TABLE 1.3 ● DIRECTIONAL AND NONDIRECTIONAL RESEARCH HYPOTHESES

Directional Research Hypothesis	Nondirectional Research Hypothesis
Students who are taught effective learning skills will perform *better* on tests than students offered incentives to do well.	Students who are taught effective learning skills will perform *differently* on tests than students offered incentives to do well.
Greater use of forceful feeding practices leads to *greater* food refusals.	Use of forceful feeding practices *leads to* food refusals.
Coercive interrogation increases eyewitnesses' false accusations.	Coercive interrogation *affects* eyewitnesses' false accusations.
Women are *less* confident in contributing to Wikipedia than are men.	Women are *different* in confidence in contributing to Wikipedia than men.

LEARNING CHECK 1:

Reviewing What You've Learned So Far

Review questions

What are the main steps involved in the research process?

Why is it useful to review and evaluate theories and research before conducting a study?

What are the two main characteristics of research hypotheses?

What is the difference between an independent variable and a dependent variable?

Listed below are several research hypotheses from published studies. For each research hypothesis, identify the independent and dependent variable.

"College students will rate instructors who dress formally (i.e., business suit and tie) as having more expertise than instructors who dress casually (i.e., slacks and shirt)" (Sebastian & Bristow, 2008, p. 197).

"It was expected that . . . greater amounts of television viewing . . . would predict greater . . . posttraumatic stress symptoms" (McLeish & Del Ben, 2008, p. 417).

"We . . . hypothesized persons who estimated the HSAS level to be red (severe) or orange (high) . . . when the HSAS level was (in fact) yellow (elevated), would report greater worry about terrorism" (Eisenman et al., 2009, p. 169).

"We hypothesized that prekindergarten children who participated in the 6-week intervention would perform better (on a test of literacy skills) than their peers in a control group who did not participate in the program" (Edmonds, O'Donoghue, Spano, & Algozzine, 2009, p. 214).

example, researchers could define the population of interest for the first research hypothesis in Table 1.1 as "college students," "college students in the United States," "college students in Georgia," or "college students at the University of Georgia." Researchers typically try to define their populations as broadly as possibly (e.g., "college students in the United States" rather than "college students in Georgia") to maximize the applications or implications of their research.

It is typically difficult to collect data from all members of a population. Imagine, for example, the time and money needed to collect information from every college student in the United States! For this reason, researchers typically draw conclusions about populations based on information collected from a sample of the population. A **sample** is a subset or portion of a population. Table 1.4 describes the samples used in the four studies introduced in Table 1.1. As you can see from Table 1.4, samples greatly vary in terms of their targeted population and size (the number of participants). The extent to which the results of a study can be generalized to the target population depends on the extent to which the sample is representative of the population.

Determining How Variables Will Be Measured: Levels of Measurement

The research hypotheses described in Table 1.1 involve variables such as instructional method, frequency of food refusals, type of interrogation, and level of confidence. To conduct a research study, the researcher must determine an appropriate way to measure the variables stated in the research hypothesis. **Measurement** is the assignment of numbers or categories to objects or events according to rules.

For example, to measure the variable "height," a researcher might use "number of inches from the ground in bare feet" as a form of measurement. To measure "success in college," a student's grade point average (GPA) may be obtained from school transcripts. "Self-esteem" might be measured by having people complete a questionnaire and, on the basis of their responses, be categorized as having either "low" or "high" self-esteem. As these examples demonstrate, the result of measurement is an assignment of a number or category to each participant in the research study. Different types of variables require different forms of measurement. Consequently, researchers have identified four distinct levels for measuring variables: nominal, ordinal, interval, and ratio.

The values of variables measured at the **nominal level of measurement** differ in category or type. The word *nominal* implies having to do with "names," such that we use first and last names to distinguish between people. Gender is an example of a nominal variable, in that it consists of categories or types (male and female) rather than numeric values. In the first research hypothesis in Table 1.1, the independent variable of instructional method is measured at the nominal level, consisting of two categories: learning skills and incentives. It is important to understand that although numbers can be assigned to nominal variables, this does not allow for comparisons based on these numbers. For example, saying "1 = Male and 2 = Female" does not mean that females have "more" gender than males.

Variables measured at the **ordinal level of measurement** have values that can be placed in an order relative to the other values. Rankings (such as finishing first, second, or third in a race), size (small, medium, large, or extra large), and ratings (below average, average, or above average) are familiar examples of an ordinal scale. Ordinal scales allow researchers to indicate that one value represents more or less of a variable than do other values; however, it is not possible to specify the precise difference between values. For example, although you can say that a runner who finishes "first" in a race is faster than the runner who finishes "second," you cannot specify the exact difference between the two runners' times. Also, similar to nominal variables, assigning numbers to ordinal variables does not provide the ability to make numeric comparisons between the values of these variables.

The values of variables measured at the **interval level of measurement** are equally spaced along a numeric continuum. One example of an interval variable is the Fahrenheit scale of temperature. Here, a difference of 5 degrees has the same meaning anywhere along the scale; for example, the difference between 45°F and 50°F is the same as the difference between 65°F and 70°F. Many variables studied in the behavioral sciences (e.g., personality characteristics or attitudes) are considered to be measured at the interval level of measurement. Interval variables not only provide more precise and specific information than do ordinal variables but also fulfill the requirements of the most commonly used statistical procedures.

Variables at the **ratio level of measurement** are identical to interval variables, with one exception: Ratio scales possess what is known as a true zero point, for which the value of zero (0) represents the complete absence of the variable. Variables that describe a physical dimension (such as height, weight, distance, and time duration) typically have a true zero point. In the first research hypothesis in Table 1.1, the researchers in this study measured the variable "test performance" by recording the number of correct answers in a test of reading comprehension. Test performance is a ratio variable because it has a true zero point, where zero would indicate the complete absence of correct answers.

TABLE 1.4 ● RESEARCH HYPOTHESES AND STUDY SAMPLES

Research Hypothesis	Study Sample
Students who are taught effective learning skills will perform better on tests than students offered incentives to do well.	"109 juniors and seniors . . . enrolled in three sections of an educational psychology course" (Tuckman, 1996, p. 200).
Greater use of forceful feeding practices leads to greater food refusals.	"60 . . . families who . . . had at least one toddler between the ages of 12–36 months" (Fries, Martin, & van der Horst, 2017, p. 94).
Coercive interrogation increases eyewitnesses' false accusations.	"Sixty university undergraduates studying introductory psychology at a provincial university in the Greater Toronto Area" (Loney & Cutler, 2016, p. 31).
Women are less confident in contributing to Wikipedia than are men.	"1,598 participants (17.15% women) . . . classified as being occasional contributors to Wikipedia" (Bear & Collier, 2016, p. 258).

One advantage of ratio measurement versus interval measurement is that ratio variables allow for a greater number of comparisons among values. Consider, for example, the value 6 for the ratio variable "inches." Not only is the difference between 4 and 6 inches the same as the difference between 6 and 8 inches (thereby involving addition and subtraction, which also can be used with interval variables), 6 inches is also twice as long as 3 inches and half as long as 12 inches (involving multiplication and division). Multiplication and division comparisons cannot be made with interval variables. You cannot, for example, say that a temperature of 90°F is three times as much temperature as 30°F.

The boldfaced and italicized text in Table 1.5 illustrates how the authors of the four studies described in the earlier tables chose to measure their independent and dependent variables. As you can see, the variables in these studies have been measured in a variety of ways at different levels of measurement.

What difference does the level of measurement make? A variable's level of measurement has important implications for researchers in that it influences how research hypotheses are stated and how data are analyzed. For example, imagine you were interested in studying the variable "success in college." You could measure this variable at the *nominal* level of measurement by having faculty members classify students into one of two groups: successful or unsuccessful. Researchers typically employ nominal variables when they are interested in questions involving differences between groups, such as, "Can differences in study habits predict whether a student will be successful or unsuccessful?"

You could instead measure success in college as an *ordinal* variable by having faculty members rank their students from top to bottom. Ranking enables a researcher to study relative differences with less concern for the precise magnitude of these differences. For example, using ranked data, you could ask, "How similar are younger and older faculty members' rankings of their students?"

To study success in college using the *interval* level measurement, you could have faculty members rate each student on a scale from 1 (low) to 100 (high). You could then use these ratings to address a research question such as, "Is there a relationship between faculty members' ratings of their students and students' ratings of themselves?"

Finally, to measure success in college using the *ratio* level of measurement, you could use students' salary after graduation (in dollars) as an indicator of success. Salary is a ratio variable because it contains a true zero point. In practice, ratio variables can be used to ask many of the same questions as those involving interval variables. For example, you could ask, "Is there a relationship between faculty members' ratings of students and students' salaries after graduation?"

TABLE 1.5 ● RESEARCH HYPOTHESES AND MEASUREMENT OF VARIABLES

Research Hypothesis	Independent Variable	Dependent Variable
Students who are taught effective learning skills will perform better on tests than students offered incentives to do well.	Instructional method **Learning strategy, incentive motivation *(nominal)***	Test performance **Number of items correct *(ratio)***
Greater use of forceful feeding practices leads to greater food refusals.	Use of forceful feeding practices **Number of forceful practices *(ratio)***	Frequency of food refusals **Number of refusals *(ratio)***
Coercive interrogation increases eyewitnesses' false accusations.	Type of interrogation **Coercive, not coercive *(nominal)***	Accuracy of accusation **Accurate, inaccurate *(nominal)***
Women are less confident in contributing to Wikipedia than are men.	Biological sex **Man, woman *(nominal)***	Level of confidence **1–5 scale (1 = disagree fully, 5 = agree fully) *(ordinal)***

As you see, how researchers choose to measure their variables influences how they state their research questions and hypotheses. The level of measurement for a variable has another important implication: It helps determine the statistical procedures researchers use to analyze the data. Certain statistical procedures can be applied only to variables measured at the interval or ratio levels of measurement, whereas other procedures are appropriate for variables measured at the nominal or ordinal level. As we move from chapter to chapter of this book in order to discuss different statistics, the level of measurement of the variables being analyzed will be noted.

Selecting a Method to Collect the Data: Experimental and Nonexperimental Research Methods

In addition to drawing a sample from a population and determining how the variables in a study may be measured, the third step in collecting data is to determine the type of research method to use to collect the data on these variables. Research methods may be classified into two main types:

- experimental research methods, and
- nonexperimental research methods.

Experimental research methods. **Experimental research methods** are methods designed to test causal relationships between variables—more specifically, whether changes in independent variables produce or cause changes in dependent variables. To make inferences about cause-effect relationships, researchers conducting an experiment must first eliminate other possible causes or explanations for changes in the dependent variable besides the independent variable. If it can be claimed that a variable other than the independent variable created the observed changes in the dependent variable, the research results are said to be confounded. A **confounding variable** is a variable related to an independent variable that provides an alternative explanation for the relationship between the independent and dependent variables.

To illustrate the concept of confounding variables, consider the following question: Is there a relationship between a mother's ethnicity and the birth weight of her baby? Although research has shown differences in the birth weights of babies of different ethnicities, one study noted that some of this research did not eliminate the possibility that these differences may be partly due to differences between ethnic groups on other factors that are also associated with low birth weights, such as the mother's average age at the time of pregnancy and behaviors such as smoking and drinking (Ma, 2008). These other factors are considered confounding variables in that they provide alternative explanations for any causal relationship between ethnicity and babies' birth weights. Confounding variables make it difficult for researchers to draw firm conclusions regarding the relationship between the independent and dependent variable.

LEARNING CHECK 2:

Reviewing What You've Learned So Far

Review questions
- What is the difference between a population and a sample?
- Within the research process, what is the relationship between populations and samples?
- What are the four levels of measurement? How do they differ?

For each of the following variables, name the scale of measurement (nominal, ordinal, interval, or ratio).
- Type of school attended (public, private)
- Probability of graduating college in 4 years (0% to 100%)
- Rating of television (good, better, best)
- Number of computers in home

Researchers minimize the influence of confounding variables in two main ways. First, researchers exercise experimental control by making the research setting (i.e., characteristics of the research participants, the instruments or measures administered, the methods used to collect data) the same for all participants. In the birth weight study, for example, the research design might control for the effect of parental smoking on birth weight by only including nonsmokers in the study sample, thereby excluding those who smoke.

Another way researchers exert control over the research setting is to include a condition known as a **control group**, which is a group of participants in an experiment not exposed to the independent variable the research is designed to test. For example, if you conducted an experiment designed to examine the effects of caffeine on one's health, one group (the experimental group) might be instructed to drink coffee while a second group (the control group) drinks decaffeinated coffee. By contrasting the results of the two groups, researchers can then assess the impact of caffeinated coffee on the health of those who drink it.

Researchers cannot possibly identify and control for the effects of all potential confounding variables. Consequently, a second strategy used to minimize the influence of confounding variables is **random assignment**, which is assigning participants to each category of an independent variable in such a way that each participant has an equal chance of being assigned to each category. For example, a researcher could randomly assign a participant to the experimental or control condition of a study by flipping a coin: heads for experimental, tails for control. The purpose of random assignment is to equalize or neutralize the effects of confounding variables by distributing them equally over the levels of the independent variable.

Nonexperimental research methods. Experimental research designs are one of the best tools researchers have for making causal inferences. However, the ability to make causal inferences requires a great deal of control over the situation, control that may not always be possible or desirable. For this reason, researchers often employ nonexperimental research methods (sometimes referred to as correlational research methods). **Nonexperimental research methods** are research methods designed to measure naturally occurring relationships between variables without having the ability to infer cause-effect relationships. Some of the most common types of nonexperimental research designs include quasi-experiments, survey research, observational research, and archival research.

Quasi-experimental research compares naturally formed or preexisting groups rather than employing random assignment to conditions. For example, suppose a researcher wanted to study the effects of different methods of teaching reading on children's verbal skills. Ideally, the researcher would randomly assign a sample of schoolchildren to receive the different teaching methods. However, because children are taught together in classes, it would be difficult to have children in the same classroom receive different methods. Implementing multiple methods in the same classroom would not only place an unreasonable burden on the teacher, but the children would also see classmates being treated differently, which might influence their behavior. To address these concerns, a researcher might assign entire classrooms of children to receive a particular method. Comparing the classrooms is an example of quasi-experimental research.

Survey research methods obtain information directly from a group of people regarding their opinions, beliefs, or behavior. The goal of survey research, which can involve the use of questionnaires and interviews, is to obtain information from a sample that can then be used to represent or estimate the views of a larger population. As one example of survey research, political pollsters attempt to predict how people will vote in an election by asking a sample of voters about their preferences. Because the researcher does not directly manipulate any variables, survey research is not conducted to make causal inferences but is instead used to describe a phenomenon or predict future behavior.

Observational research is the systematic and objective observation of naturally occurring behavior or events. The purpose of observational research is to study behavior or events, with little, if any, intervention on the part of the researcher. Observational research is often used to study phenomena that the researcher cannot or should not deliberately manipulate. For example, researchers studying interpersonal conflict among children would never force children to argue with each other. One study resolved this issue by videotaping groups of adolescents discussing topics such as competition and peer pressure and then counting the number of times the adolescents teased or mocked each other (Connolly et al., 2015).

Rather than observing or measuring behavior directly, **archival research** is the use of archives (records or documents of the activities of individuals, groups, or organizations) to examine research questions or hypotheses. One example of an archival research study studied the question of whether men are perceived to be more creative than women (Proudfoot, Kay, & Koval, 2015). In this study, the 100 most viewed talks on TED.com were identified, and the researchers compared viewers' posted ratings of the talks given by men versus those given by women.

Labeling variables in nonexperimental research. One issue that often confuses students when learning about nonexperimental research is related to the practice of referring to the variables as the "independent variable" and the "dependent variable." For example, in the study described above that involved biological sex and TED.com ratings, biological sex may be called the "independent variable" and TED.com ratings the "dependent variable." However, because biological sex isn't manipulated by the researcher, it would be inappropriate to say that biological sex "causes" differences in TED.com ratings. To avoid confusion, researchers sometimes refer to the independent variable and the dependent variable in a nonexperimental study as the **predictor variable** and **criterion variable**, respectively.

An example of combined experimental and nonexperimental research. Both experimental and nonexperimental research methods have strengths and weaknesses. The strength of experimental research is the ability to demonstrate cause-effect relationships between independent and dependent variables; however, the control that experiments require creates situations that may not resemble the real world. Nonexperimental research methods don't allow the researcher to make causal inferences; however, they have the advantage of allowing researchers to study variables as they naturally occur. Given the strengths and limitations of both research methods, one solution is to compare the findings from both methods in examining the same question.

Does playing violent video games lead to aggressive behavior? Two researchers addressed this important question by using both experimental and nonexperimental research methods, saying, "We chose two different methodologies that have strengths that complement each other and surmount each others' weaknesses" (Anderson & Dill, 2000, p. 776).

For their experiment, participants were randomly assigned to play either a violent video game or a nonviolent game; "type of video game" was their independent variable. Next, they played another type of game in which they could punish their opponent (who was actually a computer) by delivering a loud blast of noise. The loudness and duration of the noise delivered by participants represented the dependent variable of "aggressive behavior."

For their nonexperimental method, the researchers used a survey methodology, asking students to fill out a questionnaire about the number of hours they played violent video games each week (the predictor variable). For the criterion variable of aggressive behavior, students reported the number of times in the previous year that they had performed different aggressive acts, such as hitting or stealing from other students.

What did the researchers find? In reporting their findings, they wrote, "In both a correlational investigation using self-reports of real-world aggressive behaviors and an experimental investigation using a standard, objective laboratory measure of aggression, violent video game play was positively related to increases in aggressive behavior" (Anderson & Dill, 2000, p. 787). In evaluating their study, they noted the advantages of using both types of research methods, explaining that the nonexperimental method "measured video game experience, aggressive personality, and delinquent behavior in real life . . . [whereas] an experimental methodology was also used to more clearly address the causality issue" (p. 782).

Analyzing the Data

Once data collection has been completed, the next step in the research process involves data analysis. This part of the research process addresses the primary topic of this book: statistics. Because this is the first chapter of this book, we will not describe analyzing data in detail. Instead, we introduce the notion that there are two main purposes of analyzing data: (1) to organize, summarize, and describe data that has been collected and (2) to test and draw conclusions about ideas and hypotheses. These two purposes are met by calculating two main types of statistics: descriptive statistics and inferential statistics.

Calculating Descriptive Statistics

Descriptive statistics are statistics used to summarize and describe a set of data for a variable. For example, you have probably heard of crime statistics and unemployment statistics, statistics used to describe or summarize certain aspects of our society. Using a research-related example, Caitlin Abar, a researcher at Brown University, conducted a study examining increases in students' alcohol-related behaviors after entering college (Abar, 2012). To measure students' level of alcohol use, she created a variable called "typical weekend drinking," which "was measured as the sum of drinks consumed on a typical Friday and Saturday within the past 30 days" (p. 22). One way to summarize students' responses to the typical weekend drinking variable would be to calculate the mean, which is the mathematical average of a set of scores. The mean, described in Chapter 3, is an example of a descriptive statistic. The first part of this book describes a variety of descriptive statistics used by researchers to summarize data they have collected.

Calculating Inferential Statistics

Besides summarizing and describing data, a second purpose of statistics is to test hypotheses and draw conclusions. **Inferential statistics** are statistical procedures used to test hypotheses and draw conclusions from data collected during research studies. Using inferential statistics, researchers make inferences about the relationships between variables in populations based on information gathered from samples of the population.

As an example of an inferential statistic, let's return to the example of students' alcohol-related behaviors introduced above (Abar, 2012). This study was interested in seeing whether there was a relationship between these behaviors and aspects of these students' relationships with their parents. One aspect was "alcohol communications," defined as "the extent that they discussed alcohol related topics with their parents at some point during the past several months" (p. 22). To test a hypothesis regarding the relationship between alcohol communications and students' alcohol use, we could use an inferential statistic known as the Pearson correlation coefficient, which will be discussed in Chapter 13. The chapters in the last half of this book discuss a broad variety of inferential statistics, along with detailed instructions for analyzing and drawing conclusions from statistical data and presenting research findings.

Drawing a Conclusion Regarding the Research Hypothesis

Once statistical analyses have been completed, the next step is to interpret the results of the analyses as they relate to the study's research hypothesis. More specifically, do the findings of the analyses support or not support the research hypothesis? The word *support* in the previous sentence is very important. Students and researchers are sometimes tempted to conclude that their findings "prove" their hypotheses are either "true" or "false." However, as we'll discuss in Chapter 5, because researchers typically don't collect data from the entire population, they can't know with 100% certainty whether their hypothesis is in fact proven to be true or false. Also, given the complexity of the phenomena studied by researchers, it is extremely difficult for any one research study to prove a hypothesis is completely true or false. Drawing appropriate conclusions from statistical analyses is critical for building and testing theories that are based on the findings of research studies.

Communicating the Findings of the Study

Conducting research requires a variety of different skills: conceptual skills to develop research hypotheses, methodological skills to collect data, and mathematical skills to analyze these data. Another integral part of the research process is the communication skills needed to inform others about a study. Researchers must be not only skilled scientists but also effective writers.

LEARNING CHECK 3:

Reviewing What You've Learned So Far

Review questions

- What are the main differences between experimental and nonexperimental research methods?
- What are confounding variables? What do researchers do to minimize the effects of confounding variables?
- What are the main types of nonexperimental research methods?
- What are the relative strengths and weaknesses of experimental and nonexperimental research?
- What are the main purposes of descriptive and inferential statistics?

For many years, the American Psychological Association (APA), the professional association for psychologists, has provided researchers guidance on how to communicate the results of their research. In 1929, the APA published a seven-page article in the journal *Psychological Bulletin* entitled, "Instructions in Regard to Preparation of Manuscript." In contrast, the sixth edition of the *Publication Manual of the American Psychological Association,* published in 2010, consists of 272 pages. This increase in length highlights the challenges faced by writers to communicate their research in an effective and efficient manner.

1.4 PLAN OF THE BOOK

The primary purpose of this chapter was to introduce statistics and place it within the larger research process. The remainder of the book will discuss a number of different statistical procedures used by researchers to examine various questions of interest. Although it is critical for you to be able to correctly calculate statistics, it is equally important to understand the role of statistics within the research process and appreciate the conceptual and pragmatic issues related to the use (and sometimes misuse) of statistics.

The first half of the book (Chapters 2 through 6) introduces conceptual and mathematical issues that are the foundation of statistical analyses. Chapters 2, 3, and 4 discuss how data may be examined, described, summarized, and presented in numeric, visual, and graphic form. Descriptive statistics are introduced and discussed in these chapters. Chapters 5 and 6 introduce critical assumptions about and characteristics of the inferential statistical procedures used to test research hypotheses. The chapters in the second half of the book cover a number of different inferential statistical procedures, along with key issues surrounding the use of these procedures.

In most cases, the chapters in this book share a uniform format and structure and are centered on the research process. In making our presentation, we will provide various examples of actual published research studies that address questions with which you may be familiar. For each example, we will clearly state the research hypothesis, briefly describe how the data in the study were collected, introduce and describe the calculation of both descriptive and inferential statistics, and discuss the extent to which the results of the statistical analyses support the research hypothesis. Finally, we will illustrate how to communicate one's research to a broader audience.

1.5 LOOKING AHEAD

We began our presentation by defining statistics and providing reasons why learning about them may be of value to you. Next, we placed statistics within the stages of the larger research process, a process that will be the foundation of this textbook. As we have explained, the research process is centered on a research hypothesis, a predicted relationship between variables. Once a hypothesis has been stated, the next step is to collect data about the variables included in the research, after which the process of statistical analysis begins. Analyzing data involves the calculation of two main types of statistics, one designed to describe and summarize the data for a variable (descriptive statistics) and one designed to test research hypotheses (inferential statistics). However, before conducting analyses on a set of data, there is preliminary work that must be completed. The next chapter will focus on methods used by researchers to examine data.

1.6 Summary

Statistics may be defined as a branch of mathematics dealing with the collection, analysis, interpretation, and presentation of masses of numerical data. As such, statistics not only is concerned about how data are analyzed but also recognizes the importance of understanding how data are collected and how the results of analyses are interpreted and communicated. There are a variety of reasons why students should learn statistics: Statistics are encountered in a wide variety of daily activities, students may be asked or required to read and interpret the results of statistical analyses in their courses, students may use statistics in conducting their own research, and statistics may help one's career.

Researchers conduct research using the ***scientific method*** of inquiry, a method of investigation that uses the objective and systematic collection and analysis of empirical data to test theories and hypotheses. The research process used within the scientific method of inquiry consists of five main steps: developing a research hypothesis to be tested, collecting data, analyzing the data, drawing a conclusion regarding the research hypothesis, and communicating the findings to the study.

A ***research hypothesis*** is a statement regarding an expected or predicted relationship between variables. Developing a research hypothesis involves identifying a question or issue to be examined, reviewing and evaluating relevant theories and research, and stating the research hypothesis to be tested in the study. A ***theory*** is a set of propositions used to describe or explain a phenomenon. A research hypothesis contains ***variables***, which are properties or characteristics of some object, event, or person that can take on different values. More specifically, a research hypothesis states the nature and direction of a proposed relationship between an ***independent variable*** (a variable manipulated or controlled by the researcher) and a ***dependent variable*** (a variable measured by the researcher that is expected to change or vary as a function of the independent variable).

Collecting data involves drawing a sample from a population, determining how the variables will be measured, and selecting a method to collect the data. A ***population*** is the total number of possible units or elements that could potentially be included in a study; a ***sample*** is a subset or portion of a population. Variables can be measured at one of four levels of measurement: ***nominal*** (values differing in category or type), ***ordinal*** (values placed in an order relative to the other values), ***interval*** (values equally spaced along a numeric continuum), or ***ratio*** (values equally spaced along a numeric continuum with a true zero point).

There are two main types of methods used to collect data: ***experimental research methods***, designed to test whether changes in independent variables produce or cause changes in dependent variables, and ***nonexperimental research methods***, designed to examine the relationship between variables without the ability to infer cause-effect relationships.

In experimental research, researchers are concerned about possible ***confounding variables***, which are variables related to independent variables that provide an alternative explanation for the relationship between independent and dependent variables. To minimize the impact of confounding variables, a research study may exercise experimental control over various aspects of the situation, including the use of a ***control group***, which is a group of participants not exposed to the independent variable the research is designed to test, or ***random assignment***, which involves assigning participants to each category of an independent variable in such a way that each participant has an equal chance of being assigned to each category.

Examples of nonexperimental research methods are ***survey research***, in which information is directly obtained from a group of people regarding their opinions, beliefs, or behavior; ***observational research***, which involves the systematic and objective observation of naturally occurring events; and ***archival research***, which uses archives (records or documents of the activities of individuals, groups, or organizations) to examine research questions or hypotheses. In nonexperimental research, the independent variable and dependent variable may be referred to as the ***predictor variable*** and ***criterion variable***, respectively.

Once data have been collected, the next step is to analyze them using two main types of statistics: ***descriptive statistics***, which summarize and describe a set of data, and ***inferential statistics***, which are statistical techniques used to test hypotheses and draw conclusions from data collected during research studies.

Once the statistical analyses have been completed, the results of the analyses are interpreted regarding whether they support or not support the study's research hypothesis. The final step in the research process is to communicate the study to a broader audience.

1.7 Important Terms

statistics (p. 1)
scientific method (p. 3)
research hypothesis (p. 3)
variable (p. 3)
theory (p. 4)
independent variable (p. 5)
dependent variable (p. 5)
population (p. 6)
sample (p. 7)
measurement (p. 7)
level of measurement (nominal, ordinal, interval, ratio) (p. 8)
experimental research methods (p. 10)
confounding variable (p. 10)
control group (p. 11)
random assignment (p. 11)
nonexperimental research methods (p. 11)
quasi-experimental research (p. 11)
survey research (p. 11)
observational research (p. 11)
archival research (p. 12)
predictor variable (p. 12)
criterion variable (p. 12)
descriptive statistics (p. 13)
inferential statistics (p. 13)

1.8 Exercises

1. Listed below are a number of hypothetical research hypotheses. For each hypothesis, identify the independent and dependent variable.
   a. Male drivers are more likely to exhibit "road rage" behaviors such as aggressive driving and yelling at other drivers than are female drivers.
   b. The more time a student takes to finish a midterm examination, the higher his or her score on the examination.
   c. Men are more likely to be members of the Republican political party than are women; women are more likely to belong to the Democratic political party than are men.
   d. Students who receive a newly designed method of teaching reading will display higher scores on a test of comprehension than the method currently used.
   e. The more time a child spends in daycare outside of the home, the less he or she will be afraid of strangers.
2. Listed below are a number of research questions and hypotheses from actual published articles. For each hypothesis, identify the independent and dependent variable.
   a. "The use of color in a Yellow Pages advertisement will increase the perception of quality of the products for a particular business when compared with noncolor advertisements" (Lohse & Rosen, 2001, p. 75).
   b. "We hypothesized that parents who use more frequent corporal and verbal punishment . . . will report more problem behaviors in their children" (Brenner & Fox, 1998, p. 252).
   c. "It was hypothesized that adolescents with anorexia nervosa would . . . be more respectful when compared with peers with bulimia nervosa" (Pryor & Wiederman, 1998, p. 292).
   d. "The purpose of the present research was to assess brand name recognition as a function of humor in advertisements. . . . It was predicted that participants would recognize product brand names that had been presented with humorous advertisements more often than brand names presented with nonhumorous advertisements" (Berg & Lippman, 2001, p. 197).

e. "The purpose of this study was to explore the relation between time spent in daycare and the quality of exploratory behaviors in 9-month-old infants . . . it was hypothesized that . . . infants who spent greater amounts of time in center-based care would demonstrate more advanced exploratory behaviors than infants who did not spend as much time in center-based care" (Schuetze, Lewis, & DiMartino, 1999, p. 269).

f. "It was hypothesized that students would score higher on test items in which the narrative contains topics and elements that resonate with their daily experiences versus test items comprised of material that is unfamiliar" (Erdodi, 2012, p. 172).

3. Listed below are additional research questions and hypotheses from actual published articles. For each hypothesis, identify the independent and dependent variable.

   a. "It is expected that achievement motivation will be a positive predictor of academic success" (Busato, Prins, Elshout, & Hamaker, 2000, p. 1060).

   b. "Men are expected to employ physical characteristics (particularly those that are directly related to sex) more often than women in selecting dating candidates" (Hetsroni, 2000, p. 91).

   c. "The purpose of our study was to gain a better understanding of the relationship between social functioning and problem drinking. . . . We predicted that problem drinkers would endorse more social deficits than nonproblem drinkers" (Lewis & O'Neill, 2000, pp. 295–296).

   d. "We predicted that people in gain-framed conditions would show greater intention to use sunscreen . . . than those people in loss-framed conditions" (Detweiler, Bedell, Salovey, Pronin, & Rothman, 1999, p. 190).

   e. "Students with learning disabilities who received self-regulation training would obtain higher reading comprehension scores than students (with learning disabilities) in the control group" (Miranda, Villaescusa, & Vidal-Abarca, 1997, p. 504).

   f. "We hypothesized that consumers would think that a 'sale price' presentation would generate a greater monetary savings than an 'everyday low price' presentation" (Tom & Ruiz, 1997, p. 403).

   g. "We hypothesize that physical coldness (vs. warmth) would activate a need for psychological warmth, which in turn increases consumers' liking of romance movies" (Hong & Sun, 2012, p. 295).

4. Name the scale of measurement (nominal, ordinal, interval, ratio) for each of the following variables:

   a. The amount of time needed to react to a sound

   b. Gender

   c. Score on the Scholastic Aptitude Test (SAT)

   d. Political orientation (not at all conservative, conservative, very conservative)

   e. Political affiliation (Democrat, Republican, Independent)

5. Name the scale of measurement (nominal, ordinal, interval, ratio) for each of the following variables:

   a. One's age (in years)

   b. Size of soft drink (small, medium, large, extra large)

   c. Voting behavior (in favor vs. against)

   d. IQ score

   e. Parent (mother vs. father)

6. A faculty member wishes to assess the relationship between students' scores on the Scholastic Aptitude test (SAT) and their performance in college.

   a. What is a possible research hypothesis in this situation?

   b. What are the independent and dependent variables?

   c. How could you measure the variable "performance in college" at each of the four levels of measurement?

7. A researcher hypothesizes that drivers who use cellular phones will get into a greater number of traffic accidents than drivers who do not use these phones. For this example,
    a. What are the independent and dependent variables?
    b. How could you measure the dependent variable?
    c. How could you conduct this study using an experimental research method? How could you conduct this study using a nonexperimental method?

Answers to Learning Checks

Learning Check 1

1. a. IV: Instructor's dress; DV: Expertise
    b. IV: Amount of television viewing; DV: Posttraumatic stress symptoms
    c. IV: Estimation of HSAS level; DV: Worry about terrorism
    d. IV: Participation in intervention program; DV: Literacy skills

Learning Check 2

2. a. Nominal
    b. Ratio
    c. Ordinal
    d. Ratio

Answers to Odd-Numbered Exercises

1. a. Independent variable (IV): Gender; dependent variable (DV): "Road rage" behaviors
    b. IV: Time; DV: Exam score
    c. IV: Gender; DV: Political affiliation
    d. IV: Method of teaching; DV: Comprehension test scores
    e. IV: Time in daycare; DV: Fear of strangers
3. a. IV: Achievement motivation; DV: Academic success
    b. IV: Gender; DV: Emphasis on physical characteristics
    c. IV: Alcohol drinking; DV: Social deficits
    d. IV: Framing; DV: Intention to use sunscreen
    e. IV: Training program; DV: Reading comprehension scores
    f. IV: Price presentation; DV: Perception of savings
    g. IV: Physical temperature; DV: Liking of romance movies
5. a. Ratio
    b. Ordinal
    c. Nominal
    d. Interval
    e. Nominal

7. a. IV: Cellular phone use; DV: Number of traffic accidents
   b. Example: Determine the number of traffic accidents each person has experienced in the past year.
   c. Example of experimental: Use a driving simulation with the “driver” talking on a phone and measure the number of potential driving mistakes or accidents.

      Example of nonexperimental: Take a survey of the number of accidents people have been in and whether or not they were using a phone during the accident.

2

EXAMINING DATA: TABLES AND FIGURES

CHAPTER OUTLINE

Chapter 1 described a process by which scientific research may be conducted. This process begins by stating a research hypothesis regarding an expected relationship between variables. The next step involves collecting data, data that will ultimately be used in statistical analyses designed to test the research hypothesis. However, researchers do not conduct statistical analyses until they have first examined the data to ensure appropriate conclusions can be drawn from the analyses. This chapter describes why researchers examine data and how data may be examined using tables, charts, and graphs. As with many of the chapters in this book, this discussion will be guided by the findings from a published research study.

2.1 AN EXAMPLE FROM THE RESEARCH: WINNING THE LOTTERY

A friend of yours flips a coin and asks you to guess whether the coin has landed "heads" or "tails." You guess "tails," but the answer is "heads." Your friend flips the coin a second time, and again you predict "tails." But again the answer is "heads." On the third coin flip, you guess "tails" once more—but once again you are wrong. As your friend prepares to flip the coin a fourth time, you tell yourself there is little chance the coin could land on "heads" again. But the reality is that the fourth coin flip is equally likely to be "heads" or "tails." This is because the outcome of the first three coin flips has absolutely no impact on the outcome of the fourth flip. The outcome of a coin flip is a random event that cannot be controlled or predetermined. But do you really believe this?

The impact of random events can take on greater significance than the outcome of a coin flip. For example, some government-run lotteries provide the opportunity to win huge amounts of money through the random selection of numbers. In 2001, Dr. Karen Hardoon, a researcher at McGill University in Canada, studied the thought processes people might use when purchasing lottery tickets (Hardoon, Baboushkin, Derevensky, & Gupta, 2001). As previous research had found some gamblers believe they can control random events such as the rolling of dice or the spinning of a roulette wheel, Dr. Hardoon and her colleagues were interested in determining "whether individuals with gambling problems perceive the purchase of lottery tickets in a similar manner as non-problem gamblers" (p. 752). On the basis of the earlier findings, Dr. Hardoon hypothesized that problem gamblers are less likely to believe lottery outcomes are random than are non–problem gamblers.

To test their research hypothesis, Dr. Hardoon and her associates located a group of gamblers and asked whether they had ever experienced problems as a result of their gambling. The research team then classified the participants into two groups: problem gamblers and non–problem gamblers.

Each participant in the study, which we will refer to as the lottery study, was shown four lottery tickets and was asked, "If you were to buy a ticket to play in the lottery, which one would you select?" Each ticket contained six numbers selected from among the numbers 1 through 49; the four tickets were given a particular label. The *sequence* ticket had numbers in consecutive order (30-31-32-33-34-35); numbers on the *pattern* ticket increased by 5s (5-10-15-20-25-30); the *nonequilibrated* numbers (35-37-40-43-44-49) were clustered at the upper end of the 49 numbers, and the *random* ticket (7-8-23-34-36-42) shared none of the characteristics of the other three tickets. We will call the variable in this study "lottery ticket," a variable with four values or categories: sequence, pattern, nonequilibrated, and random.

The researchers recorded which of the four tickets was chosen by each participant. Table 2.1 lists the data for the lottery ticket variable for the non–problem gamblers (the data for the problem gamblers in the study are provided in the exercises at the end of this chapter). Looking at this table, we see that the non–problem gamblers differed in their lottery ticket choices; however, it is difficult to describe the extent or nature of these differences given the unorganized nature of the collected data. Consequently, before conducting any statistical analyses on their data, researchers typically organize and examine them. In the following sections, we will discuss why and how data are organized and examined.

2.2 WHY EXAMINE DATA?

There are a variety of reasons why researchers examine data they have collected before conducting statistical analyses on the data. These reasons include the following:

- to gain an initial sense of the data,
- to detect data coding or data entry errors,
- to identify outliers,
- to evaluate research methodology, and
- to determine whether data meet statistical criteria and assumptions.

Each of these reasons is discussed below.

TABLE 2.1 ⬢ THE LOTTERY TICKET CHOICES OF 22 NON–PROBLEM GAMBLERS

Participant	Lottery Ticket	Participant	Lottery Ticket	Participant	Lottery Ticket
1	Random	9	Pattern	17	Nonequilibrated
2	Random	10	Pattern	18	Random
3	Nonequilibrated	11	Random	19	Random
4	Pattern	12	Pattern	20	Pattern
5	Random	13	Random	21	Random
6	Sequence	14	Nonequilibrated	22	Random
7	Random	15	Random		
8	Random	16	Pattern		

Gaining an Initial Sense of the Data

Researchers spend a great amount of time and energy designing their research studies; consequently, they are eager to analyze the data they collect so that they may test their research hypotheses. Students taking courses in statistics, on the other hand, face a different challenge: They are given sets of data with which they have no prior experience and have only a short amount of time to learn and apply statistical formulas to the data. Although both researchers and students may be motivated to analyze their data as quickly as possible, it is important to first examine the data in order to gain an initial sense of them.

As an example, imagine you conduct a study regarding the fuel efficiency of automobiles. In your study, you collect data on the miles per gallon (MPG) of different types of cars. You might expect the scores in your data set to range from 10 to 40 MPG, with the majority of scores between 15 and 25 MPG. Examining data helps researchers gain an initial sense of the data they have collected and whether the data are in line with their expectations. Examining data also provides a way of confirming the results of later statistical analyses. We've found that students' errors in their calculations could have been avoided had they first looked at the set of data. For example, examining data will help you avoid making statements such as, "The MPG for the cars in my sample ranged from 10 to 324 MPG," "The average GPA in my sample of college students was 6.36," or "The students in my sample owned an average of 13.24 cellphones."

Detecting Data Coding or Data Entry Errors

Another reason for examining data before conducting statistical analyses is to detect any errors made in the coding of data that have been collected. Imagine, for example, that a group of students is asked to complete a 20-item test of mathematical calculations; each student's score on the test is the number of items answered correctly. Once the test scores are calculated, they are entered into a computer file. In this situation, it's crucial to ensure that no mistakes are made in calculating the test scores or in data entry. Data coding and data entry errors are not at all uncommon. Left unattended, seemingly minor errors can lead to a great loss of time and energy—including the need, in some cases, to repeat the statistical analysis of the data.

Identifying Outliers

Researchers also examine their data to identify **outliers**, defined as rare, extreme scores that lie outside of the range of the majority of scores in a set of data. Returning to our example of the 20-item test of mathematical calculations, suppose the test is given to 15 students. In scoring the tests, a researcher finds that 14 students correctly answered between 8 and 17 questions. However, one student provided the wrong answer to every question on the test, for a score of 0. In this case, the score of 0 would be considered an outlier.

If not identified, outliers may distort conclusions researchers draw about their sample and their data, particularly when the sample is relatively small. In the above example, the single score of 0 might lead an observer to conclude the class as a whole performed more poorly on the test than they actually did.

Evaluating Research Methodology

Examining data is also useful in assessing the effectiveness of the methods researchers use to collect their data. For the 20-item math test, for example, the possible scores range from 0 to 20 questions answered correctly. Having administered the test to 15 students, it might be reasonable to expect the majority of scores to fall in the middle of the 0 to 20 range. But what if every student answered at least 16 of the 20 questions correctly? Based on such a finding, we might conclude the test was too easy and that more questions are needed to accurately assess students' level of knowledge. By comparing the collected data for a variable with the range of possible values, researchers are able to evaluate and modify their measurement tools.

Determining Whether Data Meet Statistical Criteria and Assumptions

Researchers also examine their data to see whether they meet certain statistical criteria and assumptions. Many of the statistical procedures discussed in this book are based on specific assumptions regarding the shape and nature of a set of data that has been collected. These procedures generally assume, for example, that in most data sets, the majority of the data points will fall in the middle of the range of possible values, with a relatively small amount of data at the highest and lowest possible values. In the example of the 20-item math test, it might be assumed that most scores will be between 7 and 13, with smaller number of scores either less than 7 or greater than 13. When assumptions such as this are not met, it is more likely a researcher may draw inappropriate conclusions from any statistical analyses that are conducted.

2.3 EXAMINING DATA USING TABLES

One part of examining data that have been collected for a variable involves answering a series of questions:

- What are the values of the variable?
- How many participants in the sample have each value of the variable?
- What percentage of the sample has each value of the variable?

As it would be difficult to answer questions such as these just by looking at the data in Table 2.1, researchers typically organize their data by creating a table known as a **frequency distribution table**, a table that summarizes the number and percentage of participants for the different values of a variable. This section discusses the steps involved in creating frequency distribution tables using the questions listed above.

What Are the Values of the Variable?

The first step in organizing the data for a variable is to identify all of the possible values for the variable. Table 2.2 begins the construction of a frequency distribution table by listing the four values for the lottery ticket variable.

How Many Participants in the Sample Have Each Value of the Variable?

Once the values of the variable have been identified, the next step in organizing data that have been collected is to determine the **frequency** of each value, which is the number of participants in a sample corresponding to a

TABLE 2.2 ⬢ IDENTIFYING THE VALUES OF THE LOTTERY TICKET VARIABLE

Lottery Ticket
Sequence
Pattern
Nonequilibrated
Random

TABLE 2.3 ⬢ USING THE TICK MARK METHOD TO DETERMINE THE FREQUENCIES OF THE LOTTERY TICKET VARIABLE

Lottery Ticket	Tick Marks	*f*
Sequence	I	1
Pattern	卌 I	6
Nonequilibrated	III	3
Random	卌 卌 II	12
Total		22

value of a variable. These frequencies provide an indication of the nature and shape of the distribution of values for a variable in a sample.

One way to determine the frequencies for a variable is to sort the data into the different values and then count the number of participants having each value using a "tick mark method." Using this method, a tick mark is placed next to a value of the variable each time that value appears in the sample. As shown in Table 2.3, the tick marks are then counted to determine the frequency for each value. For example, the number of tick marks and therefore the frequency (f) for the sequence ticket is 1 because it was picked by one participant (Participant 6 in Table 2.1). Similarly, the tick marks for each of the other three types of tickets can be recorded and counted until all of the data in the sample have been accounted for.

What Percentage of the Sample Has Each Value of the Variable?

Although it is important to determine the frequency for each value of a variable, these frequencies by themselves are not always particularly informative. For example, the statement "There are 35 Democrats in my sample" may be interpreted differently depending on whether the total sample consists of 40 voters versus 400 voters.

Because the interpretation of frequencies depends on the size of the sample, it is useful to calculate the percentage of the sample having each value of a variable. These percentages can be calculated using the following formula:

$$\% = \frac{f}{total\ number\ of\ scores} * 100 \qquad (2\text{-}1)$$

where f is the frequency for a value of a variable.

From Table 2.3, we found that 1 of the 22 non–problem gamblers chose the sequence ticket. Therefore, the percentage of the sample choosing the sequence ticket is

$$\% = \frac{f}{total\ number\ of\ scores} * 100$$
$$= \frac{1}{22} * 100 = .05 * 100$$
$$= 5\%$$

After calculating the percentage for each of the four tickets, Table 2.4 provides the frequency distribution table for the lottery ticket variable.

Once a frequency distribution table has been constructed for a variable, researchers can begin to draw conclusions about the data in their sample. For the lottery ticket variable, the random ticket had the highest frequency and percentage (f = 12, 54%) compared to the pattern (f = 6, 27%), nonequilibrated (f = 3, 14%), and sequence (f = 1, 5%) tickets. As a result, the researchers in the lottery study made the following observation:

> The results of the present study indicated that, for the entire sample, the most commonly cited reason for selecting a lottery ticket was perceived randomness. Furthermore, with respect to actual ticket selections, irrespective of explanations, the greatest percentage of tickets selected by the entire sample . . . were random tickets. (Hardoon et al., 2001, p. 760)

TABLE 2.4 ● FREQUENCY DISTRIBUTION TABLE FOR THE LOTTERY TICKET VARIABLE

Lottery Ticket	*f*	%
Sequence	1	5%
Pattern	6	27%
Nonequilibrated	3	14%
Random	12	54%
Total	22	100%

LEARNING CHECK 1:

Reviewing What You've Learned So Far

Review questions

What are some reasons for examining data before conducting statistical analyses?

Why are outliers of concern to researchers?

What questions do you address about a set of data for a variable in constructing frequency distribution tables?

Why is it useful to calculate percentages in addition to frequencies for each value of a variable?

For each of the following situations, create a frequency distribution table.

A college counselor asks a group of 116 seniors what their plans are after graduating from college; 71 say they are going to "work," 34 are planning on going to "graduate school," and 11 say they are "not sure" what their plans are.

(Continued)

(Continued)

A high school instructor teaching a course finds that of the students she teaches, 69 are Freshmen, 18 are Sophomores, 12 are Juniors, and 9 are Seniors.

A pollster stops 12 people and asks if they are either "in favor" or "against" a local proposition:

Person	Position	Person	Position	Person	Position
1	In favor	5	Against	9	In favor
2	In favor	6	Against	10	Against
3	Against	7	In favor	11	In favor
4	In favor	8	Against	12	In favor

The company that makes M&Ms candy (www.mms.com) conducted a survey asking people which new color they would like to have added: purple, aqua, or pink. Below are the votes of a hypothetical sample:

Person	Color	Person	Color	Person	Color	Person	Color
1	Pink	7	Purple	13	Pink	19	Aqua
2	Purple	8	Aqua	14	Purple	20	Purple
3	Pink	9	Purple	15	Aqua	21	Purple
4	Aqua	10	Pink	16	Pink	22	Pink
5	Purple	11	Aqua	17	Purple	23	Pink
6	Purple	12	Pink	18	Purple	24	Purple

2.4 GROUPED FREQUENCY DISTRIBUTION TABLES

The frequency distribution table for the lottery ticket variable in Table 2.4 was sufficient for presenting the frequencies for each of the four lottery ticket choices. However, other situations may involve numeric variables with a large number of possible values. Consider, for example, the variable grade point average (GPA). The values for GPA typically range from 0.00 to 4.00, with hundreds of possible values in between. Creating a frequency distribution table for a variable such as GPA would result in an extremely large table, with many values having frequencies of zero.

To examine a variable with a large number of values, it is often useful to construct a **grouped frequency distribution table**, a table that groups the values of a variable measured at the interval or ratio level of measurement into a small number of intervals and then provides the frequency and percentage for each interval. To illustrate how grouped frequency distribution tables are constructed, Table 2.5(a) provides a sample of 42 hypothetical GPAs. In Table 2.5(b), each of these 42 GPAs has been placed into one of eight intervals that comprise a grouped frequency distribution table.

To illustrate how to read and interpret a grouped frequency distribution table, the lowest interval in Table 2.5(b) consists of students with GPAs less than (<) 2.00. The frequency in this interval ($f = 1$) consists of one student: Student 29 (GPA = 1.96). The next interval consists of students with GPAs ranging from 2.00 to 2.29 and contains three students (4, 22, and 38). This grouping continues until all of the GPAs in the sample have been accounted for.

To create a grouped frequency distribution table, the real limits of each interval need to be identified. The **real limits** of an interval are the values of the variable that fall halfway between the top of one interval and the bottom of the next interval. For example, because of how values of GPA are rounded, the lowest value of GPA that would lead someone to be placed in the interval 2.30–2.59 is not 2.30 but rather 2.295, which is halfway between the top of the 2.00–2.29 interval and the bottom of the 2.30–2.59 interval. The **real lower limit** is the smallest value of a variable that would be grouped into a particular interval. In this case, 2.295 represents the real lower limit for the 2.30–2.59 interval. On the other hand, the **real upper limit** is the largest value of a variable that would be grouped into a particular interval. For the 2.30–2.59 interval, the real upper limit is 2.594. This is the real upper limit because it falls halfway between the top of this interval (2.59) and the bottom of the next interval (2.60).

Once the grouped frequency table for the GPA example has been created (Table 2.5(b)), what preliminary conclusions might be drawn about these students? First, because the 2.90–3.19 interval has the greatest frequency ($f = 10$), you might conclude that the typical student in this sample has a GPA close to 3.00. Second, moving in both directions away from the 2.90–3.19 interval, the frequencies of the different intervals grow progressively smaller, with fewer and fewer students receiving either very high or very low GPAs.

Table 2.6 provides a list of guidelines for creating grouped frequency distribution tables. Grouped frequency distribution tables are useful in summarizing variables that have a large number of values. However, by combining values of a variable, these tables provide little detail and specificity about individual values. For example, although Table 2.5(b) reveals that 10 students have GPAs in the 2.90–3.19 interval, it does not provide the exact GPA of any particular student. For example, there is no way of determining whether any student had a GPA of exactly 3.00.

Cumulative Percentages

In addition to determining the percentage of the sample that has each individual value or interval for a variable, it is sometimes useful to combine these percentages. For the GPA example, you may be interested in knowing, "What percentage of the sample had GPAs less than 2.60?" To answer this question, the percentages in the "%" column of the frequency distribution table must be combined. This type of percentage is referred to as a **cumulative percentage**, defined as the percentage of a sample at or below a particular value of a variable.

TABLE 2.5 ⬢ GRADE POINT AVERAGE (GPA), 42 STUDENTS

a. Individual GPAs

Student	GPA	Student	GPA	Student	GPA	Student	GPA
1	**3.05**	12	**3.10**	23	**2.65**	34	**2.71**
2	**2.83**	13	**3.06**	24	**3.40**	35	**3.43**
3	**3.26**	14	**3.83**	25	**2.87**	36	**3.95**
4	**2.19**	15	**2.39**	26	**2.92**	37	**3.32**
5	**3.52**	16	**3.16**	27	**2.89**	38	**2.28**
6	**3.34**	17	**3.92**	28	**3.41**	39	**3.08**
7	**3.02**	18	**2.37**	29	**1.96**	40	**3.25**
8	**2.97**	19	**3.65**	30	**3.77**	41	**2.40**
9	**3.71**	20	**3.70**	31	**3.20**	42	**3.22**
10	**2.50**	21	**3.00**	32	**2.86**		
11	**2.77**	22	**2.26**	33	**2.94**		

(Continued)

TABLE 2.5 ⬢ (CONTINUED)

b. Grouped Frequency Distribution Table

GPA	*f*	%
3.80+	3	7%
3.50–3.79	5	12%
3.20–3.49	9	21%
2.90–3.19	10	24%
2.60–2.89	7	17%
2.30–2.59	4	10%
2.00–2.29	3	7%
< 2.00	1	2%
Total	42	100%

TABLE 2.6 ⬢ GUIDELINES FOR CREATING GROUPED FREQUENCY DISTRIBUTION TABLES

1. *Variables are grouped into approximately 10 intervals.*

   The exact number of intervals depends on the data in each sample. For example, data that fall within a small range of values may be accurately represented with a relatively small number of intervals, whereas data extending across a wide range may require a larger number of intervals.

2. *The number of intervals should accurately represent the data.*

   The intervals should represent the nature of the data as accurately as possible. For example, there should not be so large a number of intervals that many intervals have frequencies of zero (e.g., 3.00–3.05) or so few intervals that a large majority of the sample falls into only one or two intervals (e.g., 3.00–3.99).

3. *Intervals should be of equal size.*

   To make the intervals comparable, they should be of equal size or width. For example, you would not want one interval of 2.01–2.50 (a width of .50) and another of 2.51–2.70 (a width of .20). One exception to this guideline is the lowest or highest interval (e.g., less than 2.00 or greater than 3.70), which is typically wider than the others because it contains a relatively small frequency.

4. *Intervals should not overlap.*

   Each interval should be distinct from the other intervals, such that each score is included in only one interval. For example, you would not want one interval to be 2.30–*2.60* and the next to be *2.60*–2.90 because the GPA 2.60 appears in both intervals. This would lead to confusion regarding which interval to place someone with a GPA of 2.60.

Table 2.7 includes the cumulative percentages for the GPA example. As an example of a cumulative percentage, the cumulative percentage for the 2.30–2.59 interval (19%) has been calculated by combining the percentages for the < 2.00, 2.00–2.29, and 2.30–2.59 intervals (2% + 7% + 10% = 19%). As a result, we could conclude that 19% of this sample had GPAs less than 2.60. The accumulating of percentages continues until all (100%) of the scores in the sample are combined. As shown in Table 2.7, cumulative percentages are typically located in the final column of a frequency distribution table and labeled "Cum %." Although we used a grouped frequency distribution table to illustrate cumulative percentages, cumulative percentages may also be calculated for frequency distribution tables in which the values for the variable are not grouped.

TABLE 2.7 ● FREQUENCY DISTRIBUTION TABLE WITH CUMULATIVE PERCENTAGES FOR THE GPA VARIABLE

GPA	*f*	%	Cum %
3.80+	3	7%	**100%**
3.50–3.79	5	12%	**93%**
3.20–3.49	9	21%	**81%**
2.90–3.19	10	24%	**60%**
2.60–2.89	7	17%	**36%**
2.30–2.59	4	10%	**19%**
2.00–2.29	3	7%	**9%**
< 2.00	1	2%	**2%**
Total	42	100%	

2.5 EXAMINING DATA USING FIGURES

In addition to organizing data into frequency distribution tables, researchers also examine data visually using figures such as charts or graphs. There are four types of figures often used to visually portray data for variables:

- bar charts,
- pie charts,
- histograms, and
- frequency polygons.

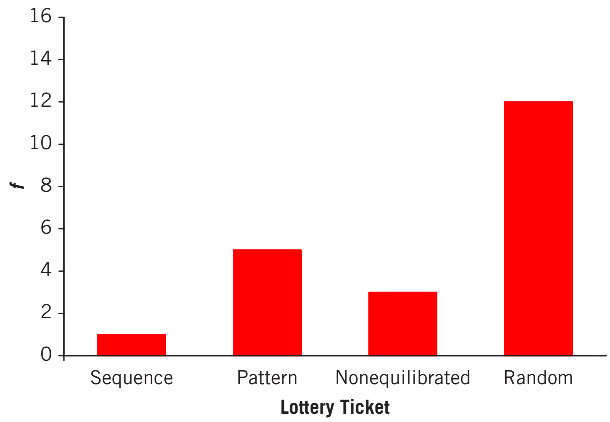
Which type of figure a researcher may use depends on the variable's level of measurement (nominal, ordinal, interval, ratio). Data for variables measured at the nominal or ordinal level of measurement are typically displayed using bar charts or pie charts. The values of interval and ratio variables are graphed using histograms and frequency polygons. Each of these types of visual illustration is discussed below.

Displaying Nominal and Ordinal Variables: Bar Charts and Pie Charts

The values of variables measured at the nominal level of measurement differ in category or type; one example of a nominal variable is the lottery ticket variable discussed earlier, which consisted of four categories: sequence, pattern, nonequilibrated, and random. The values of variables measured at the ordinal level of measurement can be placed in an order relative to the other values; age (young, middle age, elderly) is one example of an ordinal variable.

One way to display nominal and ordinal variables is to use a bar chart. A **bar chart** is a figure that uses bars to represent the frequency or percentage of a sample corresponding to each value of a variable, with the different bars not touching each other. Figure 2.1 shows a bar chart for the data from the lottery ticket variable. In this figure, each bar corresponds to one of the four types of lottery tickets; the height of each bar corresponds to the frequency (f) of non–problem gamblers who selected that type of ticket.

FIGURE 2.1 ● BAR CHART SHOWING THE FREQUENCIES OF THE LOTTERY TICKET VARIABLE FOR THE NON–PROBLEM GAMBLERS



When creating a bar chart, the values of the variable are placed along the horizontal (X) axis and the frequency (f) or percentage (%) for each value is placed along the vertical (Y) axis. Note that the different bars in the bar chart in Figure 2.1 do not touch or intersect. The gap between bars indicates that the values of the variable represent distinct groups or categories that cannot be connected together along a numeric continuum.

A second type of figure used to display nominal or ordinal variables is a pie chart. A **pie chart** is a figure that uses a circle divided into proportions to represent the percentage of the sample for each value of a variable. Pie charts are created by dividing the 360 degrees of a circle into pieces (or proportions) corresponding to the percentage of each value.

Figure 2.2 shows a pie chart for the data for the lottery ticket variable. To illustrate how pie charts are constructed, the frequency distribution table in Table 2.4 shows that 5% of non–problem gamblers chose the sequence ticket. Given that a pie chart is a circle consisting of 360 degrees, 5% of the 360 degrees are needed to represent the sequence ticket. As 5% * 360 = 18, 18 degrees of the pie is assigned to the sequence ticket. Similarly, 97 degrees of the pie chart (27% of 360) are used to represent the pattern ticket. This process continues until all 360 degrees of the pie chart are accounted for.

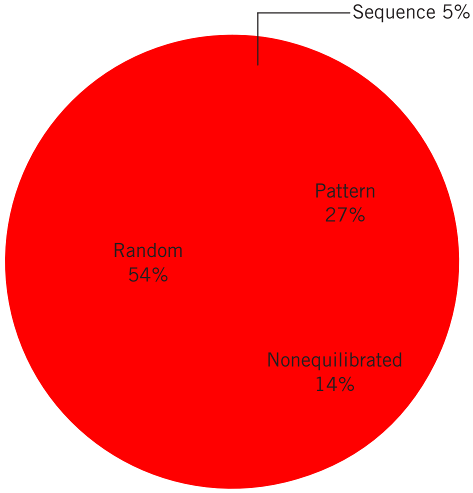
Displaying Interval and Ratio Variables: Histograms and Frequency Polygons

Interval and ratio variables have values equally spaced along a numeric continuum and are identical to each other with one exception: Ratio scales possess a true zero point, for which the value of zero represents the complete absence of the variable. Examples of ratio variables include weight (measured in pounds) and speed (measured in miles per hour). The values of interval and ratio variables may be illustrated by using histograms and frequency polygons, the choice of which depends on the number of values for the variable.

A **histogram** is a figure in which bars are used to represent the frequency of each value of a variable, with the different bars touching each other. The values of the variable are located on the X-axis, and the frequency or percentage for each value is on the Y-axis. Histograms are similar to bar charts, with one important difference: The bars in a histogram touch each other, indicating that the values of the variable are connected to each other along a numeric continuum.

Imagine a teacher is interested in studying aggressive behavior in children. She decides to measure this variable by counting the number of fights each of her students is involved in during a 3-day period. "Number of fights" is a ratio variable with a small number of values; it is a ratio rather than interval variable because the

FIGURE 2.2 ⬢ PIE CHART SHOWING THE PERCENTAGES OF THE LOTTERY TICKET VARIABLE FOR THE NON–PROBLEM GAMBLERS



value of 0 represents the complete absence of fights. Figure 2.3 provides a frequency distribution table and histogram for this variable.

A histogram is used when an interval or ratio variable consists of a relatively small number of values. But what if, for example, the number of fights could be anywhere from 0 to 20 rather than 0 to 5? In order to have the histogram fit on one page, the 21 bars would need to be very thin and crowded together, making the histogram confusing and difficult to read. In situations such as this, the values of the variable may be more clearly illustrated using a figure known as a frequency polygon. A **frequency polygon** is a line graph that uses data points to represent the frequency of each value of a variable, with lines connecting the data points. In a frequency polygon, the X-axis represents the values of the variable, while the Y-axis represents the frequency for each value.

FIGURE 2.3 ⬢ FREQUENCY DISTRIBUTION TABLE AND HISTOGRAM FOR THE NUMBER OF FIGHTS VARIABLE

# Fights	*f*
4	1
3	2
2	5
1	1
0	3
Total	12

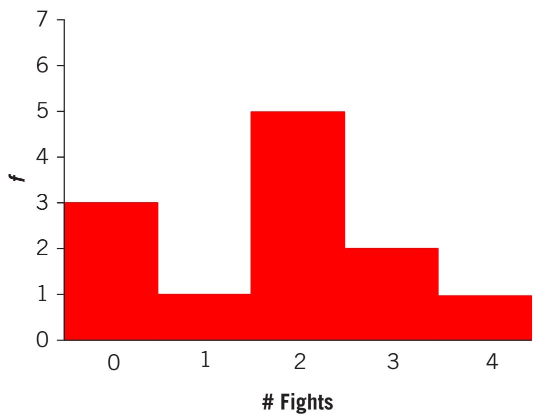


FIGURE 2.4 ● FREQUENCY POLYGON SHOWING THE FREQUENCY OF STUDENTS IN EACH INTERVAL OF THE GRADE POINT AVERAGE (GPA) VARIABLE

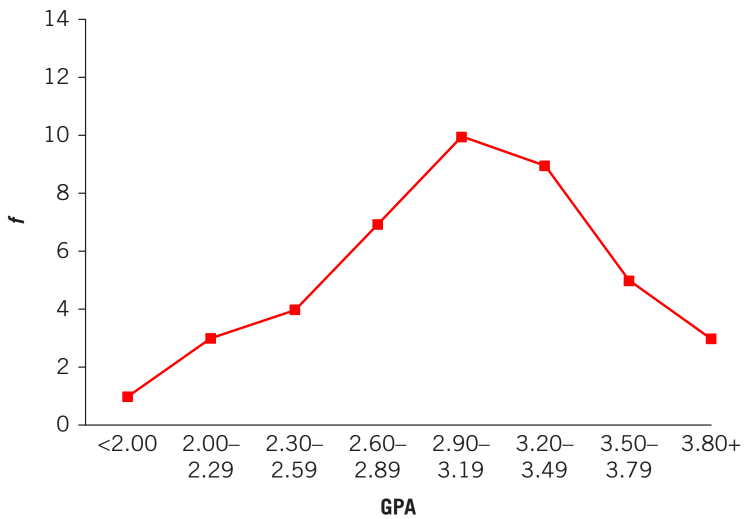


Figure 2.4 shows a frequency polygon based on the grouped frequency distribution table of the earlier example of students' GPA (Table 2.5(b)). In this frequency polygon, the data points representing the frequencies of the eight GPA intervals are connected using straight, sharp lines. These lines indicate that the values of the variable can be connected together along a numeric continuum.

Although a frequency polygon like the one in Figure 2.4 may look jagged as it moves from one data point to the next, it provides a general sense of the shape of the distribution of scores for a variable. For example, looking at Figure 2.4, you might conclude that the majority of GPAs in this sample are in the middle of the 1.00 to 4.00 range, with relatively low frequencies of students with either low or high GPAs.

LEARNING CHECK 2:

Reviewing What You've Learned So Far

Review questions

- What is the difference between a frequency distribution table and a grouped frequency distribution table?
- For what levels of measurement would you create a pie chart, bar chart, histogram, or a frequency polygon?
- What is the difference between a bar chart and a histogram?
- Why would it be inappropriate to create a histogram or frequency polygon for a nominal or ordinal variable?
- Under what circumstances might you use a frequency polygon rather than a histogram to graph an interval or ratio variable?

For each of the following variables, identify whether you could use a bar chart, pie chart, histogram, and/or a frequency polygon to visually display the data.

- Miles per gallon (MPG)
- Living situation (on-campus, off-campus)
- Number of brothers and sisters
- Marital status (single, married, divorced)