

The background of the cover is composed of numerous overlapping, flowing, and swirling lines in a variety of colors including purple, blue, orange, yellow, and red. These lines create a sense of dynamic movement and depth, framing the central text.

EDITION

2

AN INTRODUCTION TO
STATISTICS

An Active Learning Approach

Kieth A. Carlson | Jennifer R. Winquist



	<i>z for a Sample Mean</i>	<i>Single-Sample t</i>	<i>Related t</i>	<i>Independent t</i>	<i>Correlation</i>
Research Situation	Testing difference between a sample mean (e.g., $M = 98$) and a population mean; σ known (e.g., $\mu = 100$, $\sigma = 15$)	Testing difference between a sample mean (e.g., $M = 98$) and a population mean; σ unknown (e.g., $\mu = 100$, $\sigma = ?$)	Testing difference between two related sample means (e.g., pre vs. post)	Testing difference between two sample means collected from different groups (e.g., men vs. women)	Testing relationship between two interval/ratio variables—Pearson; if either is ordinal—Spearman
1. Assumptions	-Appropriate measurement -Normality -Independence -Homogeneity of variance	-Appropriate measurement -Normality -Independence -Homogeneity of variance	-Appropriate measurement -Normality -Independence	-Appropriate measurement -Normality -Independence -Homogeneity of variance	For Pearson -Appropriate measurement -Normality -Independence -Homoscedasticity -Linear relationship
2. Hypotheses	Two-tailed $H_0: \mu = 100; H_1: \mu \neq 100$ One-tailed $H_0: \mu \leq 100; H_1: \mu > 100$ OR $H_0: \mu \geq 100; H_1: \mu < 100$	Two-tailed $H_0: \mu = 100; H_1: \mu \neq 100$ One-tailed $H_0: \mu \leq 100; H_1: \mu > 100$ OR $H_0: \mu \geq 100; H_1: \mu < 100$	Two-tailed $H_0: \mu_0 = 0; H_1: \mu_0 \neq 0$ One-tailed $H_0: \mu_0 \leq 0; H_1: \mu_0 > 0$ OR $H_0: \mu_0 \geq 0; H_1: \mu_0 < 0$	Two-tailed $H_0: \mu_1 = \mu_2; H_1: \mu_1 \neq \mu_2$ One-tailed $H_0: \mu_1 \leq \mu_2; H_1: \mu_1 > \mu_2$ OR $H_0: \mu_1 \geq \mu_2; H_1: \mu_1 < \mu_2$	Two-tailed $H_0: \rho = 0; H_1: \rho \neq 0$ One-tailed $H_0: \rho \leq 0; H_1: \rho > 0$ OR $H_0: \rho \geq 0; H_1: \rho < 0$ $df = N - 2$
3. Critical region	If two-tailed, $\alpha = .05$, CV = 1.96 or -1.96 If one-tailed, $\alpha = .05$, CV = 1.65 or -1.65	$df = N - 1$	$df = N - 1$		
4. Test statistic	$SEM_p = \frac{\sigma}{\sqrt{N}}$ $z = \frac{M - \mu}{SEM_p}$	$SEM_s = \frac{SD}{\sqrt{N}}$ $t = \frac{M - \mu}{SEM_s}$	$SEM_t = \frac{SD_0}{\sqrt{N}}$ $t = \frac{M_0}{SEM_t}$	$SD_p^2 = \frac{(n_1 - 1)SD_1^2 + (n_2 - 1)SD_2^2}{(n_1 - 1) + (n_2 - 1)}$ $SEM_i = \sqrt{\frac{SD_p^2}{n_1} + \frac{SD_p^2}{n_2}}$ $t = \frac{(M_1 - M_2)}{SEM_i}$	$SS_{xy} = \Sigma XY - \frac{(\Sigma X)(\Sigma Y)}{N}$ $r = \frac{SS_{xy}}{\sqrt{(SS_x)(SS_y)}}$

	<i>z</i> for a Sample Mean	Single-Sample <i>t</i>	Related <i>t</i>	Independent <i>t</i>	Correlation
5. Effect size	$d = \frac{M - \mu}{\sigma}$ <p>.2, .5, .8</p>	$d = \frac{M - \mu}{SD}$ <p>.2, .5, .8</p>	$d = \frac{M_0}{SD_0}$ <p>.2, .5, .8</p>	$d = \frac{M_1 - M_2}{\sqrt{SD_p^2}}$ <p>.2, .5, .8</p>	r^2 <p>.01, .09, .25</p>
6. Confidence intervals	<p>CI for sample mean</p> $M \pm (t_{\alpha}) \left(\frac{\sigma}{\sqrt{N}} \right)$ <p>CI for mean difference</p> $(M - \mu) \pm (t_{\alpha}) \left(\frac{\sigma}{\sqrt{N}} \right)$	<p>CI for sample mean</p> $M \pm (t_{\alpha}) \left(\frac{SD}{\sqrt{N}} \right)$ <p>CI for mean difference</p> $(M - \mu) \pm (t_{\alpha}) \left(\frac{SD}{\sqrt{N}} \right)$	<p>CI for each mean</p> $M_0 \pm (t_{\alpha}) \left(\frac{SD}{\sqrt{N}} \right)$ <p>CI for mean difference</p> $(M_1 - M_2) \pm (t_{\alpha}) \left(\frac{SD_0}{\sqrt{N}} \right)$	<p>CI for each mean</p> $M \pm (t_{\alpha}) \left(\frac{SD}{\sqrt{N}} \right)$ <p>CI for mean difference</p> $(M_1 - M_2) \pm (t_{\alpha}) \left(\frac{\sqrt{SD_p^2}}{\sqrt{N}} \right)$	<p>CI for Pearson</p> $(z_r) \pm (z_{\alpha}) \left(\frac{1}{\sqrt{N-3}} \right)$
7. Summarize	<p>There was (or was not) a significant difference between the sample mean (<i>M</i>, <i>SD</i>) and the population mean (<i>μ</i>, <i>σ</i>), <i>z</i> (<i>N</i>) = __, <i>p</i> = __, 95% CI [LB, UB]. If appropriate, indicate which mean was significantly higher and describe the effect size.</p>	<p>There was (or was not) a significant difference between the sample mean (<i>M</i>, <i>SD</i>) and the population mean (<i>μ</i>), <i>t</i> (<i>df</i>) = __, <i>p</i> = __, <i>d</i> = __, 95% CI [LB, UB]. If appropriate, indicate which mean was significantly higher and describe the effect size.</p>	<p>There was (or was not) a significant difference between the pre-treatment sample mean (<i>M</i>, <i>SD</i>) and the post treatment sample mean (<i>M</i>, <i>SD</i>), <i>t</i> (<i>df</i>) = __, <i>p</i> = __, <i>d</i> = __, 95% CI [LB, UB]. If appropriate, indicate which mean was significantly higher and describe the effect size.</p>	<p>There was (or was not) a significant difference between the Sample 1 mean (<i>M</i>, <i>SD</i>) and the Sample 2 mean (<i>M</i>, <i>SD</i>), <i>t</i> (<i>df</i>) = __, <i>p</i> = __, <i>d</i> = __, 95% CI [LB, UB]. If appropriate, indicate which mean was significantly higher and describe the effect size.</p>	<p>There was (or was not) a linear association between Variable 1 and Variable 2, <i>r</i> (<i>df</i>) = __, <i>p</i> = __, 95% CI [LB, UB].</p>
8. SPSS instructions for significance test	Not available	<p>-Analyze</p> <p>-Compare Means</p> <p>-One-Sample <i>t</i> Test</p> <p>-Move DV into the Test Variables box</p> <p>-Change Test Value to <i>μ</i></p> <p>-Click OK</p>	<p>-Analyze</p> <p>-Compare Means</p> <p>-Paired-Samples <i>t</i> Test</p> <p>-Move both IV conditions into Paired Variables box</p> <p>-Click OK</p>	<p>-Analyze</p> <p>-Compare Means</p> <p>-Independent-Samples <i>t</i> Test</p> <p>-Move IV into Grouping Variable box</p> <p>-Click Define Groups</p> <p>-Enter values that designate each IV condition</p> <p>-Move DV into Test Variables box</p> <p>-Click OK</p>	<p>For scatterplot:</p> <p>-Graph, Legacy Dialogs, Scatter/Dot.</p> <p>-Simple scatter</p> <p>-Click Define</p> <p>-Place variables on x- and y-axes</p> <p>For test:</p> <p>-Analyze, Correlate, Bivariate</p> <p>-Move variables into Variables box</p> <p>-Select Pearson or Spearman. Click OK</p>

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An Introduction to Statistics

AN ACTIVE LEARNING APPROACH

Second Edition

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Preface

THE STORY OF THIS TEXT

Several years ago, we attended a teaching workshop in which the speaker described a common experience in college classrooms and the pedagogical problems it frequently creates. Instructors carefully define basic concepts (e.g., population, sample) and gradually progress to applying those concepts to more complex topics (e.g., sampling error) as the end of class approaches. Then students attempt homework assignments covering the more complicated topics. All too frequently, students think they understand things while listening to us in class, but when they attempt homework on their own, they have difficulty. While some students can eventually figure things out, others become frustrated; still others give up. The teaching workshop made us recognize, reluctantly, this happened to us (and our students) in our statistics classes. While we did our best to address this problem by refining our lectures, our students still struggled with homework assignments, and we were disappointed with their exam performance. Students frequently said to us, “I understand it when you do it in class, but when I try it on my own it doesn’t make sense.” This common experience motivated us to change our stats classes and, eventually, to write the first edition of this text.

We decided that we needed to change our course so that

1. students came to class understanding basic concepts and
2. students had an opportunity to *use* challenging concepts in class when we were there to answer their questions immediately,
3. students started to interpret and report statistical results like researchers.

We started by emphasizing the importance of actually reading the text before class. Even though we were using excellent statistics texts, many students insisted that they needed lectures to help them understand the text. Eventually, we opted for creating our own readings that emphasize the basics (i.e., the “easy” stuff). We embedded relatively easy reading questions to help students *read with purpose* so they came to class understanding the basic concepts. Next, over several years, we developed activities that reinforced the basics as well as introduced more challenging material (i.e., the “hard stuff”). Hundreds of students completed these challenging activities in our courses. After each semester, we strove to improve every activity based on our students’ feedback and exam performance.

Our statistics courses are dramatically different from what they were a decade ago. In our old classes, few students read prior to class, and most class time was spent lecturing on the material in the book. In our current stats courses, students answer online reading questions prior to class, we give very brief lectures at the beginning of class, and students complete activities (i.e., assignments) during class.

We've compared our current students' attitudes about statistics to those taking our more traditional statistics course (Carlson & Winquist, 2011) and found our current students to be more confident in their ability to perform statistics and to like statistics more than their peers. We've also learned that after completing this revised statistics course, students score nearly a half a standard deviation higher on a nationally standardized statistics test that they take during their senior year (approximately 20 months after taking the course) compared to students taking the more traditional course (Winquist & Carlson, 2014).

Of course, not all our students master the course material. Student motivation still plays an important part in student learning. If students don't do the reading or don't work on understanding the assignments in each chapter, they will still struggle. In our current courses, we try to create a class that encourages students to read and complete the assignments by giving points for completing them. We have found that, if students do these things, they do well in our courses. We have far fewer struggling students in our current courses than we had in our traditional course, even though our exams are more challenging.

WHAT IS NEW IN THE SECOND EDITION

If you used the first edition of the text, the first thing you might notice is that the second edition has 14 chapters rather than 16, but the text is actually longer. In the first edition, all hypothesis tests followed the same five steps and statistical assumptions were addressed in Chapter 16. In the second edition, we eliminated Chapter 16 and included assessing the statistical assumptions as the first step of a six-step hypothesis-testing process. While talking about the statistical assumptions within every chapter is less concise, this repetition helps students recognize that different statistical tests analyze different types of variables. In addition, in response to reviewers' comments, we also combined Chapters 6 and 7 from the first edition into a single chapter in the second edition. Finally, in the first edition, we introduced the basics in the chapter and then added more complex material in the activities. Although this simplified the readings for students, it also made the book harder for students to use as a reference. In this edition, we include the more complex material in the chapters but kept the reading questions relatively simple. This way, students are exposed to the material prior to working with the more complex ideas in the assignments. Reflecting the rising prominence of confidence intervals in contemporary research and the most recent APA publication manual, we greatly expanded our coverage of confidence intervals in the second edition. We added integrative assignments in the related *t*, independent *t*, one-way analysis of variance (ANOVA), and correlation chapters to reinforce the different information researchers obtain from significance tests, effect sizes, and confidence intervals. These assignments encourage students to do more than "crunch numbers" by asking them to think like researchers, integrating information from significance tests, effect sizes, and confidence intervals.

Other noteworthy changes to the second edition include the following:

- New assignments are included on the hand calculations of a one-way ANOVA, running one-way ANOVA in SPSS, the differences between one-way and two-way ANOVA, and Spearman correlation.

- Twelve of the 14 chapters have been rewritten using more interesting examples from psychological research.
- Assignments contain fewer open-ended questions so students can check their own answers more accurately.
- Added coverage of effect sizes for pairwise comparisons.
- Added practice tests at the end of each chapter.

HOW TO USE THIS BOOK

This text certainly could be used in a lecture-based course in which the activities function as detailed, conceptually rich homework assignments. We also are confident that there are creative instructors and students who will find ways to use this text that we never considered. However, it may be helpful to know how we use this text. In our courses, students read the chapters and answer online reading questions prior to class. We allow them to retake the reading questions to correct any errors prior to class for half of the points they missed. We begin classes with brief lectures (about 15 minutes), and then students work for the remaining 60 minutes to complete the assignments during class. There are a number of advantages to this approach. One advantage is that students do the easier work (i.e., answering foundational questions) outside of class and complete the more difficult work in class when peers and an instructor can answer their questions. Another advantage is that students work at their own paces. We have used this approach for several years with positive results (Carlson & Winquist, 2011; Winquist & Carlson, 2014).

This approach encourages students to review and correct misunderstandings on the reading questions as well as the assignments. Mistakes are inevitable and even desirable. After all, each mistake is an opportunity to learn. In our view, students should first engage with the material without concern about evaluation. Therefore, we provide the final answers to all assignments to our students. Students then focus on finding their answers, checking them, and then correcting mistakes. We collect their answers to confirm that they showed how they arrived at each answer. We give points for completion (and showing work). Over the years, these assignment points have constituted between 7% and 17% of students' course grades. A simpler option we tried is telling students that completing the activities is essential to success in the course and not confirm activity completion at all. When we did this, we found greater variability in activity completion and exam performance.

UNIQUE FEATURES OF THIS TEXT

By now you probably recognize that this is not a typical statistics text. For ease of review, we've listed and described the two most unique aspects of this text:

- *Embedded reading questions*—All 14 chapters contain embedded reading questions that focus students' attention on the key concepts *as they read* each paragraph/section of the text. Researchers studying reading comprehension report that similar embedded questions help students with lower reading abilities achieve levels of performance comparable to that of students with greater reading abilities (Callender & McDaniel, 2007).

- *Activity (Assignment) sections*—All 14 chapters contain active learning assignments, called *Activities*. While the 14 chapters start by introducing foundational concepts, they are followed by activity sections in which students *test or demonstrate their understanding of basic concepts while they read detailed explanations of more complex statistical concepts*. When using most traditional textbooks, students perform statistical procedures *after* reading multiple pages. This text adopts a workbook approach in which students are actively performing tasks *while* they read explanations. Most of the activities are self-correcting, so if students misunderstand a concept, it is corrected early in the learning process. After completing these activities, students are far more likely to understand the material than when they simply read the material.

OTHER HELPFUL FEATURES

- *Learning objectives*—Each chapter and activity begin with clear learning objectives.
- *Practice tests*—All 14 chapters conclude with a practice test for solidifying student learning.
- *IBM® SPSS® Statistics**—All chapters contain detailed step-by-step instructions for conducting statistical procedures with SPSS as well as annotated explanations of SPSS output.
- *Emphasis on understanding*—Chapters use definitional formulas to explain the logic behind each statistical procedure and rely on SPSS for more advanced computations (e.g., factorial ANOVAs).
- *Writing results in APA format*—Many activity questions highlight how to write about statistical analyses in scholarly ways.

ANCILLARIES

- *Instructors' manual*—Includes lecture outlines and detailed answers to activities.
- *Blackboard cartridges*—Includes reading questions, practice tests, self-test questions, and activity answers.
- *Empirically validated test bank questions*—Exam questions that we used in our classes are available to instructors of the course.
- *Self-examination questions*—Additional sample examination questions are available to students on the Sage Publications website.
- *Short PowerPoint slideshows for most Activities*.

APPROPRIATE COURSES

This text is ideal for introductory statistics courses in psychology, sociology, social work, and the health, exercise, or life sciences. The text would work well for any course intending to teach the statistical procedures of hypothesis testing, effect sizes, and confidence intervals that are commonly used in the behavioral sciences.

*SPSS is a registered trademark of International Business Machines Corporation.

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CHAPTER 1

Introduction to Statistics and Frequency Distributions

LEARNING OBJECTIVES

After reading this chapter, you should be able to do the following:

- Explain how you can be successful in this course

- Use common statistical terms correctly in a statistical context

- Statistic, parameter, sample, population, descriptive statistics, inferential statistics, sampling error, and hypothesis testing

- Identify the scale of measurement of a variable (nominal, ordinal, or interval/ratio)

- Determine if a variable is discrete or continuous

- Create and interpret frequency distribution tables, bar graphs, histograms, and line graphs

- Explain when to use a bar graph, histogram, and line graph

- Enter data into SPSS and generate frequency distribution tables and graphs

HOW TO BE SUCCESSFUL IN THIS COURSE

Have you ever read a few pages of a textbook and realized you were not thinking about what you were reading? Your mind wandered to topics completely unrelated to the text, and you could not identify the point of the paragraph (or sentence) you just read. For most of us, this experience is not uncommon even when reading books that we've chosen to read for pleasure. Therefore, it is not surprising that our minds wander while reading textbooks. Although this lack of focus is understandable, it seriously hinders effective reading. Thus, one goal of this book is to discourage mind wandering and to encourage *reading with purpose*. To some extent, you need to force yourself to read with purpose. As you read each paragraph, ask, "What is the purpose of this paragraph?" or "What am I supposed to learn from this paragraph?"

**Reading
Question**

1. Reading with purpose means
 - a. thinking about other things while you are reading a textbook.
 - b. actively trying to extract information from a text by focusing on the main point of each paragraph.

This text is structured to make it easier for you to read with purpose. The chapters have frequent reading questions embedded in the text that make it easier for you to remember key points from preceding paragraphs. Resist the temptation to go immediately to the reading questions and search for answers in the preceding paragraphs. *Read first, and then answer the questions as you come to them.* Using this approach will increase your memory for the material in this text.

**Reading
Question**

2. Is it better to read the paragraph and then answer the reading question or to read the reading question and then search for the answer? It's better to
 - a. read the paragraph, then answer the reading question.
 - b. read the reading question, then search for the question's answer.

After reading the chapters, you should have a basic understanding of the material that will provide the foundation you need to work with the more complex material in the activities. When completing these activities, you will demonstrate your understanding of basic material from the reading (by answering questions) before you learn more advanced topics. Your emphasis when working on the activities should be on understanding why the answers are correct. If you generate a wrong answer, figure out your error. We often think of errors as things that should be avoided at all costs. However, quite the opposite is true. Making mistakes and fixing them is how you learn. Every error is an opportunity to learn. If you find your errors and correct them, you will probably not repeat the error. Resist the temptation to “get the right answer quickly.” It is more important that you understand why every answer is correct.

**Reading
Question**

3. Which of the following best describes the activities in this book?
 - a. Activities introduce new material that was not included in the chapter reading.
 - b. All of the new material is in the reading. The activities are simply meant to give you practice with the material in the reading.

**Reading
Question**

4. When completing activities, your primary goal should be to get the correct answer quickly.
 - a. True
 - b. False

At the end of each chapter, there is a “Practice Test.” After you complete the assigned activities in a chapter (and you understand why every answer is correct), you should complete the practice test. Most students benefit from a few repetitions of each problem type. The additional practice helps consolidate what you have learned so you don't forget it during tests. Finally, use the activities and the practice tests to study. Then, *after* you understand all of the activities and all of the practice tests, assess your understanding by taking an additional self-test on the SAGE website. Try to duplicate a testing situation as much as possible. Just sit down with a calculator and have a go at it. If you can do the self-test, you should feel confident in your knowledge of the material. Taking practice tests days before your actual test will give you time to review material if you discover you did not understand something.

Testing yourself is also a good way to lessen the anxiety that can occur during testing. Again, additional practice test questions are available on the SAGE website.

**Reading
Question**

5. How should you use the self-tests?
 - a. Use them to study; complete them open-book so you can be sure to look up all the answers.
 - b. Use them to test what you know days before the exam; try to duplicate the testing situation as much as possible.

MATH SKILLS REQUIRED IN THIS COURSE

Students often approach their first statistics course with some anxiety. The primary source of this anxiety seems to be a general math anxiety. The good news is that the math skills required in this course are fairly basic. You need to be able to add, subtract, multiply, divide, square numbers, and take the square root of numbers using a calculator. You also need to be able to do some basic algebra. For example, you should be able to solve the following equation for X : $22 = \frac{X}{3}$. [The correct answer is $X = 66$.]

**Reading
Question**

6. This course requires basic algebra.
 - a. True
 - b. False

**Reading
Question**

7. Solve the following equation for X : $30 = \frac{X}{3}$.
 - a. 10
 - b. 90

You will also need to follow the correct order of mathematical operations. As a review, the correct order of operations is (1) the operations in parentheses, (2) exponents, (3) multiplication or division, and (4) addition or subtraction. Some of you may have learned the mnemonic, *Please Excuse My Dear Aunt Sally*, to help remember the correct order. For example, when solving the following equation, $(3 + 4)^2$, you would first add $(3 + 4)$ to get 7 and then square the 7 to get 49. Try to solve the next more complicated problem. The answer is 7.125. If you have trouble with this problem, talk with your instructor about how to review the necessary material for this course.

$$X = \frac{(6-1)3^2 + (4-1)2^2}{(6-1) + (4-1)}.$$

**Reading
Question**

8. Solve the following equation for X : $X = \frac{(3-1)4^2 + (5-1)3^2}{(3-1) + (5-1)}$.
 - a. 11.33
 - b. 15.25

You will be using a calculator to perform computations in this course. You should be aware that order of operations is very important when using your calculator. Unless you are very comfortable with the parentheses buttons on your calculator, we recommend that you do one step at a time rather than trying to enter the entire equation into your calculator.

**Reading
Question**

9. Order of operations is only important when doing computations by hand, not when using your calculator.
- True
 - False

Although the math in this course should not be new, you may see new notation throughout the course. When you encounter new notation, relax and realize that the notation is simply a shorthand way of giving instructions. While you will be learning how to *interpret* numbers in new ways, the actual mathematical skills in this course are no more complex than the order of operations. The primary goal of this course is teaching you to use numbers to make decisions. Occasionally, we will give you numbers solely to practice computation, but most of the time you will use the numbers you compute to make decisions within a specific, real-world context.

WHY DO YOU HAVE TO TAKE STATISTICS?

You are probably reading this book because you are required to take a statistics course to complete your degree. Students majoring in business, economics, nursing, political science, premedicine, psychology, social work, and sociology are often required to take at least one statistics course. There are a lot of different reasons why statistics is a mandatory course for students in these varied disciplines. The primary reason is that in every one of these disciplines, people make decisions that have the potential to improve people's lives, and these decisions should be informed by data. For example, a psychologist may conduct a study to determine if a new treatment reduces the symptoms of depression. Based on this study, the researcher will need to decide if the treatment is effective or not. If the wrong decision is made, an opportunity to help people with depression may be missed. Even more troubling, a wrong decision might harm people. While statistical methods will not eliminate wrong decisions, understanding statistical methods will allow you to reduce the number of wrong decisions you make. You are taking this course because the professionals in your discipline recognize that statistical methods improve decision making and make us better at our professions.

**Reading
Question**

10. Why do many disciplines require students to take a statistics course?
- Taking a statistics course
- is a way to employ statistics instructors, which is good for the economy.
 - can help people make better decisions in their chosen professions.

STATISTICS AND THE HELPING PROFESSIONS

When suffering from a physical or mental illness, we expect health professionals (e.g., medical doctors, nurses, clinical psychologists, and counselors) to accurately diagnose us and then prescribe effective treatments. We expect them to ask us detailed questions and then to use our answers (i.e., the data) to formulate a diagnosis. Decades of research has consistently found that health professionals who use statistics to make their diagnoses are more accurate than those who rely on their personal experience or intuition (e.g., Grove & Meehl, 1996).

For example, lawyers frequently ask forensic psychologists to determine if someone is likely to be violent in the future. In this situation, forensic psychologists typically review the person's medical and

criminal records as well as interview the person. Based on the records and the information gained during the interview, forensic psychologists make a final judgment about the person's potential for violence in the future. While making their professional judgment, forensic psychologists weigh the relative importance of the information in the records (i.e., the person's behavioral history) and the information obtained via the interview. This is an extremely difficult task. Fortunately, through the use of statistics, clinicians have developed methods that enable them to optimally gather and interpret data. One concrete example is the Violence Risk Appraisal Guide (Harris, Rice, & Quinsey, 1993). The guide is a list of questions that the psychologist answers after reviewing someone's behavioral history and conducting an interview. The answers to the guide questions are mathematically combined to yield a value that predicts the likelihood of future violence. Research indicates that clinicians who use statistical approaches such as the Violence Risk Appraisal Guide make more accurate clinical judgments than those who rely solely on their own judgment (Yang, Wong, & Coid, 2010). Today, statistical procedures help psychologists predict many things, including violent behavior, academic success, marital satisfaction, and work productivity. In addition to enabling us to make better predictions, statistical procedures also help professionals determine which medical or behavioral treatments are most effective.

Reading Question

11. Decades of research indicates that professionals in the helping professions make better decisions when they rely on
 - a. statistics.
 - b. their intuition and clinical experience.

HYPOTHESIS TESTING, EFFECT SIZE, AND CONFIDENCE INTERVALS

The statistical decisions you will make in this course revolve around specific hypotheses. A primary purpose of this book is to introduce the statistical process of **null hypothesis significance testing (NHST)**, *a formal multiple-step procedure for evaluating the likelihood of a prediction, called a null hypothesis*. Knowledge of null hypothesis significance testing, also called **significance testing** or **hypothesis testing**, is fundamental to those working in the behavioral sciences, medicine, and the counseling professions. In later chapters, you will learn a variety of statistics that test different hypotheses. All the hypothesis testing procedures that you will learn are needed because of one fundamental problem that plagues all researchers—namely, the problem of sampling error. For example, researchers evaluating a new depression treatment want to know if it effectively lowers depression in all people with depression, called the population of people with depression. However, researchers cannot possibly study every depressed person in the world. Instead, researchers have to study a subset of this population, perhaps a sample of 100 people with depression. *The purpose of any sample is to represent the population from which it came*. In other words, if the 100 people with depression are a good sample, they will be similar to the population of people with depression. Thus, if the average score on a clinical assessment of depression in the population is 50, the average score of a good sample will also be 50. Likewise, if the ratio of women with depression to men with depression is 2:1 in the population, it will also be 2:1 in a good sample. Of course, you do not really expect a sample to be exactly like the population. *The differences between a sample and the population create* **sampling error**.

Reading Question

12. All hypothesis testing procedures were created so that researchers could
 - a. study entire populations rather than samples.
 - b. deal with sampling error.

**Reading
Question**

13. If a sample represents a population well, it will
 - a. respond in a way that is similar to how the entire population would respond.
 - b. generate a large amount of sampling error.

While null hypothesis significance testing is extremely useful, it has limitations. Therefore, another primary purpose of this book is to describe these limitations and how researchers address them by using two additional statistical procedures. **Effect sizes** describe the magnitude of a study's results, helping researchers determine if a research result is large enough to be useful or if it is too small to be meaningful in "real-world" situations. **Confidence intervals** identify the wide range of plausible values that might occur if sample results are applied to the entire population. Each of these statistical procedures helps researchers give meaning to the results of a significance test. In fact, the American Psychological Association (APA) publication manual recommends that researchers use effect sizes and confidence intervals whenever significance tests are used (American Psychological Association, 2010). These three statistical procedures are most beneficial when they are used side by side.

**Reading
Question**

14. Effect sizes and confidence intervals help researchers
 - a. interpret (i.e., give meaning to) the results of significance tests.
 - b. address the limitations of significance tests.
 - c. do both of the above.

TESTING CAUSAL HYPOTHESES

While this book's main goal is teaching how to use the statistical procedures of hypothesis testing, effect sizes, and confidence intervals, you should know that there is a lot more to *causal* hypothesis testing than the statistics covered in this text. In many research situations, scientists want to know if manipulating one variable (the independent variable, or IV) *causes* a change in a second variable (the dependent variable, or DV). Testing *causal* hypotheses is particularly difficult because it requires carefully designed experiments. In these experiments, researchers must (1) manipulate the IV, (2) measure the DV after IV manipulation, (3) control for extraneous variables, and (4) provide evidence of a "significant" relationship between the IV manipulation and the DV score. For example, if we wanted to test the causal hypothesis that cell phone use while driving causes poorer driving performance, we would need to manipulate the IV (i.e., cell phone use) by having people operate a driving simulator while talking on a cell phone and also while not using a cell phone. Then, we would need to measure the DV of driving performance (e.g., braking reaction time or number of times people swerve out of their lane) when using a cell versus not. In order for us to feel confident that using the cell phone caused poorer driving performance, we would need to know that the two groups of people were equally good drivers and driving in equally challenging driving conditions in terms of traffic density, weather, destination, and so on. In other words, we need to make sure the test is "fair" in that the only difference between the two groups of drivers is whether or not they were using a cell phone while they were driving. Finally, only after carefully manipulating the IV, measuring the DV, and controlling extraneous variables do we use statistics to determine if the driving performances of those using cell phones versus not are so different that it justifies concluding that cell phone use while driving *causes* poorer driving performance. While the statistics you will learn in this text are a necessary component of testing causal hypotheses, they are not all you need to know. Causal hypothesis testing also requires mastery of experimental design. In a research methods course, you will learn how to design "fair" experiments that enable you to use the statistical procedures taught in this text to test causal hypotheses.

**Reading
Question**

15. Testing casual hypotheses requires knowing how to
- use statistics.
 - use research methods to design “fair” experiments.
 - both of the above.

POPULATIONS AND SAMPLES

Suppose that a researcher studying depression gave a new treatment to a sample of 100 people with depression. Figure 1.1 is a pictorial representation of this research scenario. The large circle on the left represents a **population**, *a group of all things that share a set of characteristics*. In this case, the “things” are people, and the characteristic they all share is depression. Researchers want to know what the mean depression score for the population would be if all people with depression were treated with the new depression treatment. In other words, researchers want to know the **population parameter**, *the value that would be obtained if the entire population were actually studied*. Of course, the researchers don’t have the resources to study every person with depression in the world, so they must instead study a **sample**, *a subset of the population that is intended to represent the population*. In most cases, the best way to get a sample that accurately represents the population is by taking a **random sample** from the population. When taking a **random sample**, *each individual in the population has the same chance of being selected for the sample*. In other words, while researchers want to know a population parameter, their investigations usually produce a **sample statistic**, *the value obtained from the sample*. The researchers then use the sample statistic value as an estimate of the population parameter value. The researchers are making an *inference* that the sample statistic is a value similar to the population parameter value based on the premise that the characteristics of those in the sample are similar to the characteristics of those in the entire population. *When researchers use a sample statistic to infer the value of a population parameter*, it is called **inferential statistics**. For example, a researcher studying depression wants to know how many depressive symptoms are exhibited by people in the general population. He can’t survey everyone in the population, and so he selects a random sample of people

Figure 1.1 A Pictorial Representation of Using a Sample to Estimate a Population Parameter (i.e., Inferential Statistics)



from the population and finds that the average number of symptoms in the sample is 8 (see Figure 1.1). If he then inferred that the entire population of people would have an average of 8 depressive symptoms, he would be basing his conclusion on inferential statistics. It should be clear to you that if the sample did not represent the population well (i.e., if there was a lot of sampling error), the sample statistic would NOT be similar to the population parameter. In fact, **sampling error** is defined as *the difference between a sample statistic value and an actual population parameter value*.

**Reading
Question**

16. The value obtained from a population is called a
- statistic.
 - parameter.

**Reading
Question**

17. Parameters are
- always exactly equal to sample statistics.
 - often estimated or inferred from sample statistics.

**Reading
Question**

18. When a statistic and parameter differ,
- it is called an inferential statistic.
 - there is sampling error.

The researchers studying depression were using inferential statistics because they were using data from a sample to infer the value of a population parameter. The component of the process that makes it inferential is that researchers are using data they actually have to estimate (or infer) the value of data they don't actually have. In contrast, researchers use **descriptive statistics** *when their intent is to describe the data that they actually collected*. For example, if a clinical psychologist conducted a study in which she gave some of her clients a new depression treatment and she wanted to describe the average depression score of only those clients who got the treatment, she would be using descriptive statistics. Her intent is only to describe the results she observed in the clients who actually got the treatment. However, if she then wanted to estimate what the results would be if she were to give the same treatment to additional clients, she would then be performing inferential statistics.

**Reading
Question**

19. Researchers are using descriptive statistics if they are using their results to
- estimate a population parameter.
 - describe the data they actually collected.

**Reading
Question**

20. Researchers are using inferential statistics if they are using their results to
- estimate a population parameter.
 - describe the data they actually collected.

INDEPENDENT AND DEPENDENT VARIABLES

Researchers design experiments to test if one or more variables cause changes to another variable. For example, if a researcher thinks a new treatment reduces depressive symptoms, he could design an experiment to test this prediction. He might give a sample of people with depression the new treatment and withhold the treatment from another sample of people with depression. Later, if those who received the new treatment had lower levels

of depression, he would have evidence that the new treatment reduces depression. In this experiment, the type of treatment each person received (i.e., new treatment vs. no treatment) is the **independent variable (IV)**. In this study, the experimenter manipulated the IV by giving one sample of people with depression the new treatment and another sample of people with depression a placebo treatment that is not expected to reduce depression. In this experiment, the IV has two **IV levels**: (1) the new treatment and (2) the placebo treatment. The main point of the study is to determine if the two different IV levels were differentially effective at reducing depressive symptoms. More generally, *the IV is a variable with two or more levels that are expected to have different impacts on another variable*. In this study, after both samples of people with depression were given their respective treatment levels, the amount of depression in each sample was compared by counting the number of depressive symptoms in each person. In this experiment, the number of depressive symptoms observed in each person is the **dependent variable (DV)**. Given that the researcher expects the new treatment to work and the placebo treatment not to work, he expects the new treatment DV scores to be lower than the placebo treatment DV scores. More generally, *the DV is the outcome variable that is used to compare the effects of the different IV levels*.

Reading Question

21. The IV (independent variable) in a study is the
- variable expected to change the outcome variable.
 - outcome variable.

Reading Question

22. The DV (dependent variable) in a study is the
- variable expected to change the outcome variable.
 - outcome variable.

In true experiments, those in which researchers manipulate a variable so that some participants have one value and others have a different value, the manipulated variable is always referred to as the IV. For example, if a researcher gives some participants a drug (Treatment A) and others a placebo (Treatment B), this manipulation defines the IV of treatment as having two levels—namely, drug and placebo. However, in this text, we also use the IV in a more general way. The IV is any variable predicted to influence another variable even when the IV was not manipulated. For example, if a researcher predicted that women would be more depressed than men, we will refer to gender as the IV because it is the variable that is expected to influence the DV (i.e., depression score). If you take a research methods course, you will learn an important distinction between manipulated IVs (e.g., type of treatment: drug vs. placebo) and *measured* IVs (e.g., gender: male vs. female). Very briefly, the ultimate goal of science is to discover causal relationships, and manipulated IVs allow researchers to draw causal conclusions while measured IVs do not. You can learn more about this important distinction and its implications for drawing causal conclusions in a research methods course.

Reading Question

23. All studies allow you to determine if the IV causes changes in the DV.
- True
 - False

SCALES OF MEASUREMENT

All research is based on measurement. For example, if researchers are studying depression, they will need to devise a way to measure depression accurately and reliably. The way a variable is measured has a direct impact on the types of statistical procedures that can be used to analyze that variable. Generally speaking, researchers want to devise measurement procedures that are as precise as possible

because more precise measurements enable more sophisticated statistical procedures. Researchers recognize four different **scales of measurement** that vary in their degree of measurement precision: (1) nominal, (2) ordinal, (3) interval, and (4) ratio (Stevens, 1946). Each of these scales of measurement is increasingly more precise than its predecessor, and therefore, each succeeding scale of measurement allows more sophisticated statistical analyses than its predecessor.

Reading Question

24. The way a variable is measured
 - a. determines the kinds of statistical procedures that can be used on that variable.
 - b. has very little impact on how researchers conduct their statistical analyses.

For example, researchers could describe depression using a nominal scale by categorizing people with different kinds of major depressive disorders into groups, including those with melancholic depression, atypical depression, catatonic depression, seasonal affective disorder, or postpartum depression. **Nominal scales** of measurement *categorize things into groups that are qualitatively different from other groups*. Because nominal scales of measurement involve categorizing individuals into qualitatively distinct categories, they yield **qualitative** data. In this case, clinical researchers would interview each person and then decide which type of major depressive disorder each person has. With nominal scales of measurement, it is important to note that the categories are not in any particular order. A diagnosis of melancholic depression is not considered “more depressed” than a diagnosis of atypical depression. With all other scales of measurement, the categories are ordered. For example, researchers could also measure depression on an ordinal scale by ranking individual people in terms of the severity of their depression. **Ordinal scales** of measurement also categorize people into different groups, but on ordinal scales, these groups are rank ordered. In this case, researchers might interview people and diagnose them with a “mild depressive disorder,” “moderate depressive disorder,” or “severe depressive disorder.” An ordinal scale clearly indicates that people *differ in the amount of something they possess*. Thus, someone who was diagnosed with mild depressive disorder would be less depressed than someone diagnosed with moderate depressive disorder. Although ordinal scales rank diagnoses by severity, they do not quantify how much more depressed a moderately depressed person is relative to a mildly depressed person. To make statements about how much more depressed one person is than another, an interval or ratio measurement scale is required. Researchers could measure depression on an interval scale by having people complete a multiple-choice questionnaire that is designed to yield a score reflecting the amount of depression each person has. **Interval scales** of measurement *quantify how much of something people have*. While the ordinal scale indicates that some people have more or less of something than others, the interval scale is more precise indicating exactly *how much* of something someone has. Another way to think about this is that for interval scales, the intervals between categories are equivalent, whereas for ordinal scales, the intervals are not equivalent. For example, on an ordinal scale, the interval (or distance) between a mild depressive disorder and a moderate depressive disorder may not be the same as the interval between a moderate depressive disorder and a severe depressive disorder. However, on an interval scale, the distances between values are equivalent. If people completed a well-designed survey instrument that yielded a score between 1 and 50, the difference in the amount of depression between scores 21 and 22 would be the same as the difference in the amount of depression between scores 41 and 42. Most questionnaires used for research purposes yield scores that are measured on an interval scale of measurement. **Ratio scales** of measurement also *involve quantifying how much of something people have, but a score of zero on a ratio scale indicates that the person has none of the thing being measured*. For example, if people are asked how much money they earned last year, the income variable would be measured on a ratio scale because not only are the intervals between values equivalent, but there also is an absolute zero point. A value of zero means the complete absence of income last year. Because they involve quantifying how much of something an individual has, interval and ratio scales yield **quantitative** data. Interval and ratio scales are similar in that they both determine how much of something

someone has but some interval scales can yield a negative number, while the lowest score possible on a ratio scale is zero. Within the behavioral sciences, the distinction between interval and ratio scales of measurement is not usually very important. Researchers typically use the same statistical procedures to analyze variables measured on interval and ratio scales of measurement.

Although most variables can be easily classified as nominal, ordinal, or interval/ratio, some data are more difficult to classify. Researchers often obtain data by asking participants to answer questions on a survey. These survey responses are then combined into a single measure of the construct. For example, participants may answer a series of questions related to depression, and then the researcher would combine those questions into a single depression score. Although there is not complete agreement among statisticians, most researchers classify summed scores from questionnaires and surveys as interval data (e.g., Carifio & Perla, 2007). Thus, in this course, summed scores from surveys will be considered interval/ratio data.

Reading Question

25. Researchers typically treat summed questionnaire/survey scores as which scale of measurement?
- Nominal scale of measurement
 - Ordinal scale of measurement
 - Interval scale of measurement

When trying to identify the scale of measurement of a variable, it can also be helpful to think about what each scale of measurement allows you to do. For example, if you can only count the number of things in a given category, you know that you have a nominal scale. Table 1.1 summarizes what you can do with each type of scale and provides examples of each scale of measurement.

Table 1.1 The Four Scales of Measurement, What They Allow, and Examples

<i>Scale of Measurement</i>	<i>What the Scale Allows You to Do</i>	<i>Examples</i>
Nominal	COUNT the number of things within different categories	<i>Pets:</i> 5 dogs, 12 cats, 7 fish, 2 hamsters
		<i>Marital status:</i> 12 married, 10 divorced, 2 separated
Ordinal	COUNT & RANK some things as having more of something than others (but NOT QUANTIFY how much of it they have)	<i>Annual income:</i> above average, average, or below average
		<i>Speed (measured by place of finish in a race):</i> 1st, 2nd, 3rd, etc.
Interval	COUNT, RANK, & QUANTIFY how much of something there is, but a score of zero does not mean the absence of the thing being measured	<i>Temperature:</i> -2°F , 98°F , 57°F ; 0°F is not the absence of heat
Ratio	COUNT, RANK, & QUANTIFY how much of something there is, and a score of zero means the absence of the thing being measured	<i>Annual income:</i> \$25,048, \$48,802, \$157,435, etc.
		<i>Number of text messages sent in a day:</i> 0, 3,351, 15, etc.

**Reading
Question**

26. The scale of measurement that quantifies the thing being measured (i.e., indicates *how much* of it there is) is _____ scale(s) of measurement.
- a. the nominal
 - b. the ordinal
 - c. both the interval and ratio

**Reading
Question**

27. The scale of measurement that categorizes objects into different kinds of things is _____ scale(s) of measurement.
- a. the nominal
 - b. the ordinal
 - c. both the interval and ratio

**Reading
Question**

28. The scale of measurement that indicates that some objects have more of something than other objects but not how much more is _____ scale(s) of measurement
- a. the nominal
 - b. the ordinal
 - c. both the interval and ratio

DISCRETE VERSUS CONTINUOUS VARIABLES

Variables can also be categorized as discrete or continuous. A **discrete variable** *only occurs in whole units rather than fractions of units*. For example, the variable “number of siblings” is a discrete variable because someone can only have a whole number of siblings (e.g., no one can have 2.7 siblings). A **continuous variable** *occurs in fractions of units*. For example, the variable “time to complete a test” is a continuous variable because someone can take a fraction of minutes to complete a test (e.g., 27.39 minutes). Nominal and ordinal variables are always discrete variables. Interval and ratio variables can be either discrete or continuous.

**Reading
Question**

29. If a variable can be measured in fractions of units, it is a _____ variable.
- a. discrete
 - b. continuous

GRAPHING DATA

Graphing often helps you understand your data. For example, if you were looking at the number of siblings college students have, you could begin by looking at a graph to determine how many siblings most students have. Inspection of the graph also allows you to find out if there is anything odd in the data file that requires further examination. For example, if you graphed the data and found that most people reported having between 0 and 4 siblings but one person reported having 20 siblings, you should probably investigate to determine if that 20 was an error.

There are three basic types of graphs that we use for most data: (1) **bar graphs**, (2) **histograms**, and (3) **line graphs**. The names of the first two are a bit misleading because both are created using bars. The only difference between a bar graph and a histogram is that in a bar graph, the bars do not touch while the bars do touch in a histogram. In general, use bar graphs when the data are discrete or qualitative. The space between the bars of a bar graph emphasize that there are no possible values between any two categories (i.e., bars). For example, when graphing the number of children in a family, a bar graph is appropriate because there is no possible value between any two categories (e.g., you cannot have 1.5 children). When the data are continuous, use a histogram. For example, if you are graphing the variable “time to complete a test” and creating a bar for each minute category, the bars would touch to indicate that the variable we are graphing is continuous (i.e., 27.46 minutes is possible).

**Reading
Question**

30. What type of graph is used for discrete data or qualitative data?
- Bar graph
 - Histogram

**Reading
Question**

31. What type of graph is used for continuous data?
- Bar graph
 - Histogram

**Reading
Question**

32. In bar graphs, the bars _____.
- touch
 - don't touch

**Reading
Question**

33. In histograms, the bars _____.
- touch
 - don't touch

To create either a bar graph or a histogram, you should put categories on the x -axis and the number of scores in a particular category (i.e., the frequency) on the y -axis. For example, suppose we asked 19 students how many siblings they have and obtained the following responses:

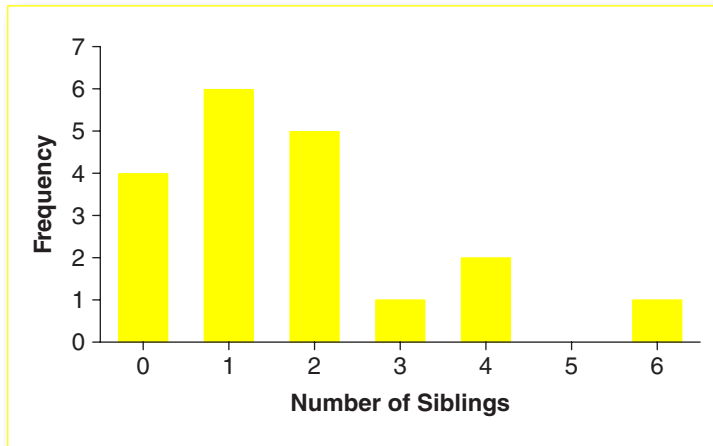
0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 3, 4, 4, 6

To graph these responses, you would list the range of responses to the question, “How many siblings do you have?” on the x -axis (i.e., in this case, 0 through 6). The y -axis is the frequency within each category. For each response category, you will draw a bar with a height equal to the number of times that response was given. For example, in the bar graph (Figure 1.2), 4 people said they had 0 siblings, and so the bar above the 0 has a height of 4.

**Reading
Question**

34. Use the graph to determine how many people said they had 1 sibling.
- 4
 - 5
 - 6

Figure 1.2 Bar Graph of Variable, Number of Siblings, Collected From a Sample of 19 Students

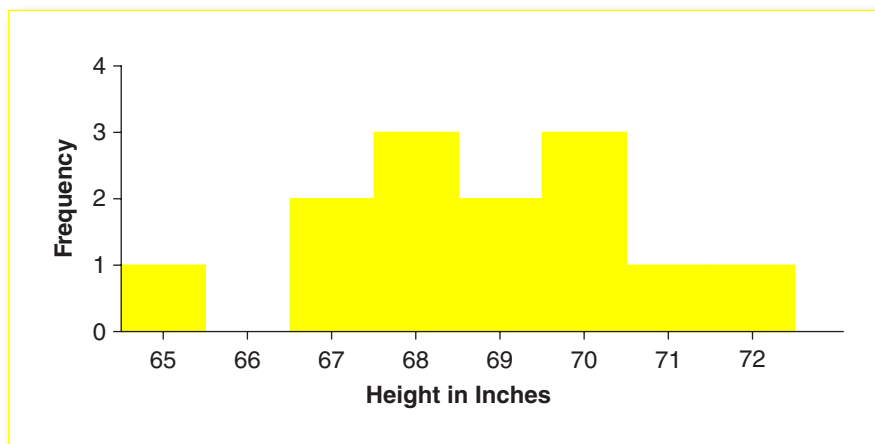


The procedure for creating a histogram is similar to that for creating a bar graph. The only difference is that the bars should touch. For example, suppose that you recorded the height of players on a volleyball team and obtained the following heights rounded to the nearest inch:

65, 67, 67, 68, 68, 68, 69, 69, 70, 70, 70, 71, 72

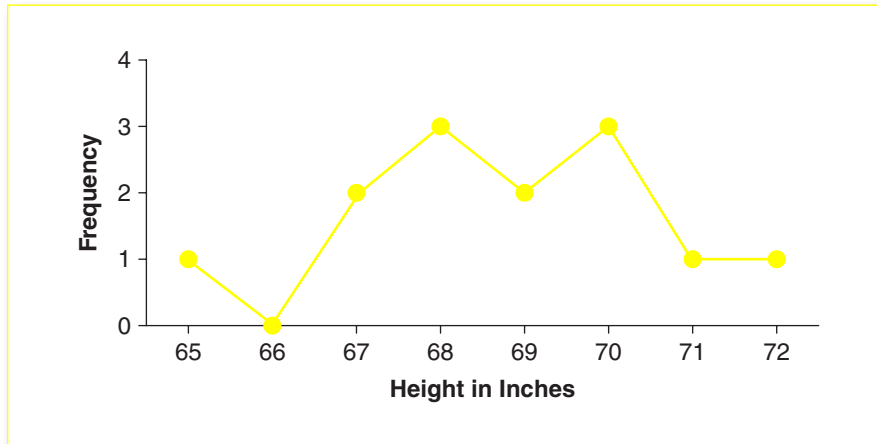
Height in inches is continuous because there are an infinite number of possible values between any two categories (e.g., between 68 and 69 inches). The data are continuous so we create a histogram (i.e., we allow the bars to touch) (Figure 1.3).

Figure 1.3 Frequency Histogram of Variable, Height in Inches, Collected From a Sample of 13 Volleyball Players



Whenever a histogram is appropriate, you may also use a **line graph** in its place. To create a line graph, you use dots to indicate frequencies and connect adjacent dots with lines (Figure 1.4).

Figure 1.4 Frequency Line Graph of Variable, Height in Inches, Collected From a Sample of 13 Volleyball Players



Whether the data are discrete or continuous should determine how the data are graphed. You should use a bar graph for discrete data and a histogram or a line graph for continuous data. Nominal data should be graphed with a bar graph. Throughout the text, we will use these guidelines, but you should be aware of the fact that histograms and bar graphs are often used interchangeably outside of statistics classes.

Reading Question

35. Line graphs can be used whenever a _____ is appropriate.

- a. histogram
- b. bar graph

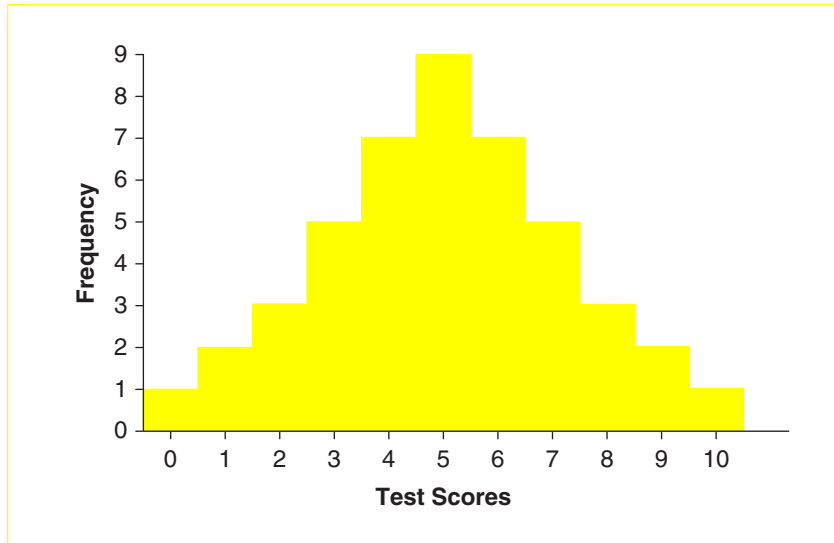
Reading Question

36. What type of graph should be used if the data are measured on a nominal scale?

- a. Histogram
- b. Bar graph

SHAPES OF DISTRIBUTIONS

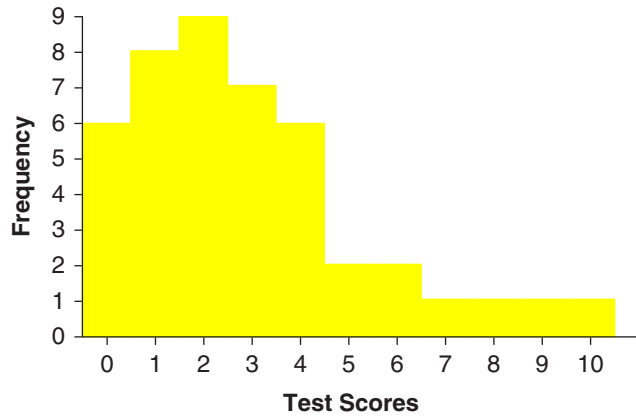
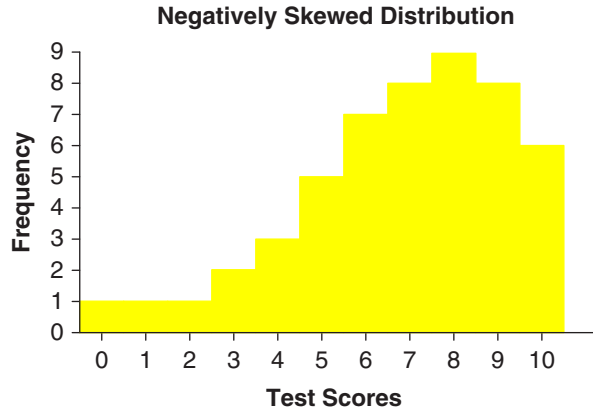
A **distribution** is a *group of scores*. If a distribution is graphed, the resulting bar graph or histogram can have any “shape,” but certain shapes occur so frequently that they have specific names. The most common shape you will see is a bell curve. The curve in Figure 1.5 resembles a bell-shaped distribution. Bell-shaped distributions are also called *normal distributions* or *Gaussian distributions*.

Figure 1.5 Frequency Histogram of Test Scores That Form a Normal Curve

One important characteristic of normal distributions is that most of the scores pile up in the middle, and as you move further from the middle, the frequency of the scores gets less. In addition, normal distributions are symmetrical in that the right and left sides of the graph are identical.

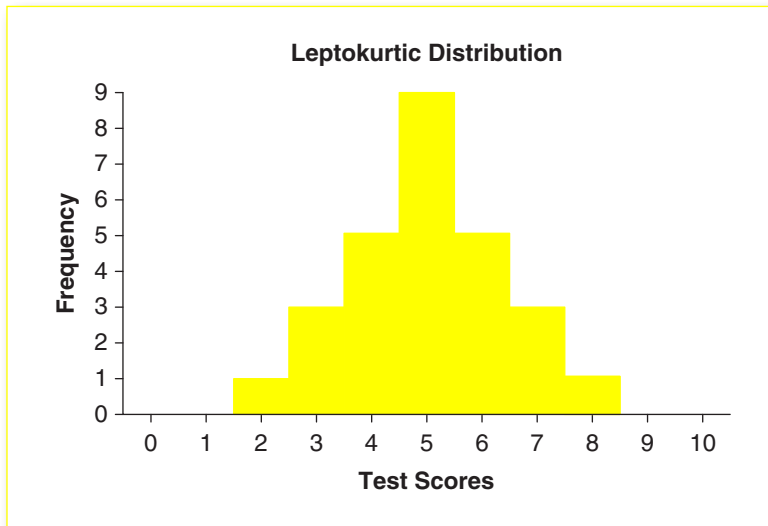
For the purposes of this book, you do not need to know the exact mathematical properties that define the normal curve. However, you should know that a normal curve looks bell shaped and symmetrical. You will use the normal curve frequently in this book.

The normal curve is important because many variables, when graphed, have a normal shape, and this fact will be very important in later chapters. While normal curves are common, there are specific ways for graphs to deviate from a normal bell shape. Some of these deviations have specific names. For example, graphs can deviate from the bell shape because of **skew**. A skewed distribution is asymmetrical, meaning the right and left sides are not identical. Instead, the scores are shifted such that most of them occur on one side of the peak with fewer scores on the other side of the scale. For example, the distributions in Figures 1.6 and 1.7 are both skewed, but in different ways. The positively skewed distribution (Figure 1.6) has the majority of the scores on the low end of the distribution with fewer scores on the higher end. The negatively skewed distribution is the opposite. Distinguishing between positive and negative skew is as easy as noticing which side of the distribution has the longer “tail” (i.e., which side takes longer to descend from the peak to zero frequency). In positively skewed distributions, the longer tail points toward the right, or the positive side of the x -axis. In negatively skewed distributions (Figure 1.7), the longer tail points toward the left, or the negative side of the x -axis. There are statistics that you can compute to quantify exactly how skewed a distribution is (see Field, 2013, for an excellent discussion), but we will just eyeball the graphs to determine if they deviate from normal.

Figure 1.6 Positively Skewed Distribution**Figure 1.7** Negatively Skewed Distribution of Scores**Reading
Question**

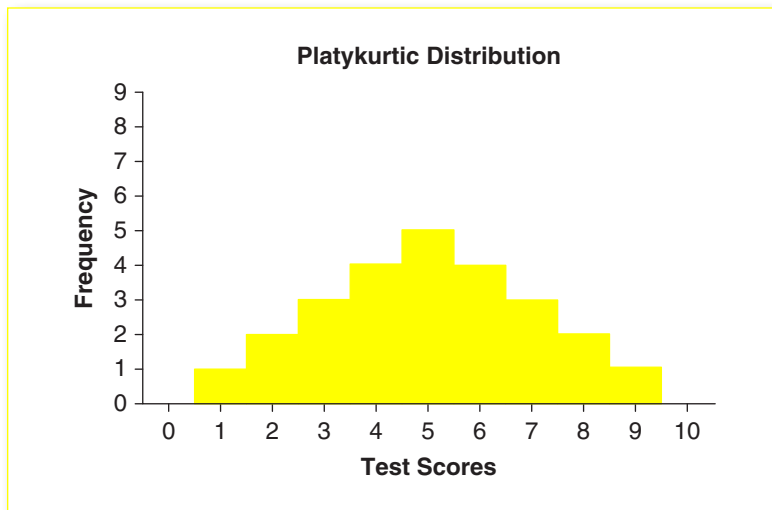
37. The scores on an exam are distributed such that most scores are low (between 30% and 50%), but a couple of people had very high scores (i.e., above 95%). How is this distribution skewed?
- Positively skewed
 - Negatively skewed

Figure 1.8 Example of a Leptokurtic Distribution



Distributions also vary in **kurtosis**, which is the extent to which they have an exaggerated peak versus a flatter appearance. Distributions that have a higher, more exaggerated peak than a normal curve are called leptokurtic, while those that have a flatter peak are called platykurtic. Figures 1.8 and 1.9 display a

Figure 1.9 Example of a Platykurtic Distribution



leptokurtic and platykurtic distribution, respectively. As with skew, there are ways to quantify kurtosis in a distribution (again, see Field, 2013), but we will just eyeball it in this book.

Reading Question

38. Distributions that are flatter than a normal distribution are called
- platykurtic.
 - leptokurtic.

FREQUENCY DISTRIBUTION TABLES

Graphing data is typically the best way to see patterns in the data (e.g., normal, leptokurtic, or platykurtic). However, some precision is often lost with graphs. Therefore, it is sometimes useful to look at the raw data in a **frequency distribution table**. To create a frequency distribution table, you need to know the measurement categories as well as the number of responses within a given measurement category. For example, suppose that a market researcher asked cell phone users to respond to the following statement: “I am very happy with my cell phone service provider.” People were asked to respond with 1 = *strongly agree*, 2 = *agree*, 3 = *neither agree nor disagree*, 4 = *disagree*, or 5 = *strongly disagree*. The responses are listed below:

1, 1, 2, 2, 2, 2, 3, 3, 3, 3, 3, 3, 4, 4, 4, 4, 4, 4, 5, 5, 5

It is probably obvious that a string of numbers like the one earlier is not a particularly useful way to present data. A frequency distribution table organizes the data, so it is easier to interpret; one is shown in Table 1.2.

The first column (X) represents the possible response categories. People *could* respond with any number between 1 and 5; therefore, the X column (i.e., the measurement categories) must include all of the *possible* response values—namely, 1 through 5. In this case, we chose to put the categories in ascending order from 1 to 5, but they could also be listed in descending order from 5 to 1.

The next column (f) is where you record the frequency of each response. For example, 4 people gave responses of 5 (*strongly disagree*) and so a 4 is written in the “ f ” column across from the response category of 5 (*strongly disagree*).

Table 1.2

Frequency Distribution Table of the Variable “I Am Very Happy With My Cell Phone Service Provider”

	X	f
Strongly agree	1	2
Agree	2	4
Neither agree nor disagree	3	7
Disagree	4	6
Strongly disagree	5	4

Reading Question

39. The value for “ f ” represents the
- number of measurement categories.
 - number of responses within a given measurement category.

Reading Question

40. In the above frequency table, how many people responded with an answer of 3?
- 2
 - 4
 - 7

SPSS

We will be using a statistical package called **SPSS (Statistical Package for the Social Sciences)** to conduct many of the statistical analyses in this course. Our instructions and screenshots were developed with Version 22. There are some minor differences between Version 22 and other versions, but you should have no difficulty using our instructions with other SPSS versions.

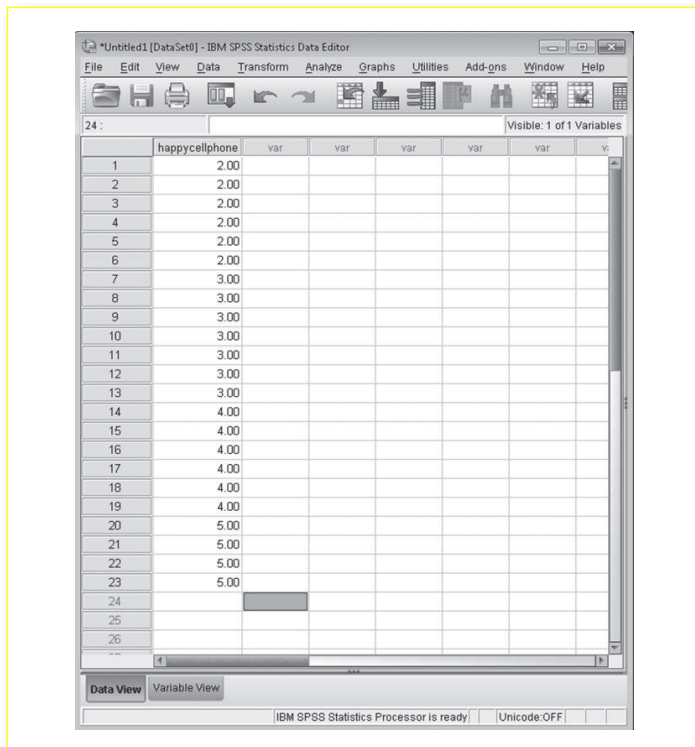
It is likely that your school has a site license for SPSS allowing you to access it on campus. Depending on your school's site license, you may also be able to access the program off campus. You may also purchase or "lease" a student or graduate version of SPSS for this course. Your instructor will tell you about the options available to you.

Data File

After you open SPSS, click on the Data View tab near the bottom left of the screen. Enter the data you want to analyze in a single column.

We have used the cell phone data from the previous page to help illustrate how to use SPSS. In Figure 1.10, a variable named "happycellphone" is shown at the top of the column of data. To add this variable name, double click on the blue box at the top of a column in the Data View screen.

Figure 1.10 Screenshot of SPSS Data Entry Screen



Doing so will take you to the Variable View screen. You can also access the Variable View screen by pressing the Variable View tab at the bottom left of the screen. In the first column and first row of the Variable View screen, type the name of the variable you want to appear in the data spreadsheet (e.g., happycellphone—the variable name cannot have spaces or start with a number). To go back to the Data View, click on the blue Data View tab at the bottom left of the screen.

The data file you created should look like the screenshot in Figure 1.10. The exact order of the data values is not important, but all 23 scores should be in a single column. As a general rule, all the data for a variable must be entered in a single column.

Reading Question

41. The Variable View screen is where you
- enter the variable names.
 - enter the data.

Reading Question

42. The Data View screen is where you
- enter the variable names.
 - enter the data.

Creating Frequency Distribution Tables and Graphs

SPSS can create frequency tables and graphs. To create a frequency graph of the data you just entered, do the following:

- From the Data View screen, click on Analyze, Descriptive Statistics, and then Frequencies.
- To create a graph, click on the Charts button and then choose the type of graph you want to create (Bar chart, Pie chart, or Histogram). Click on the Continue button.
- Be sure that the Display Frequency Tables box is checked if you want to create a frequency distribution table.
- Click on the OK button to create the frequency distribution table and graph.

After performing the steps outlined above, a frequency distribution graph and table will appear in the SPSS output screen. Use the SPSS output provided in Figure 1.11 to answer the following three questions.

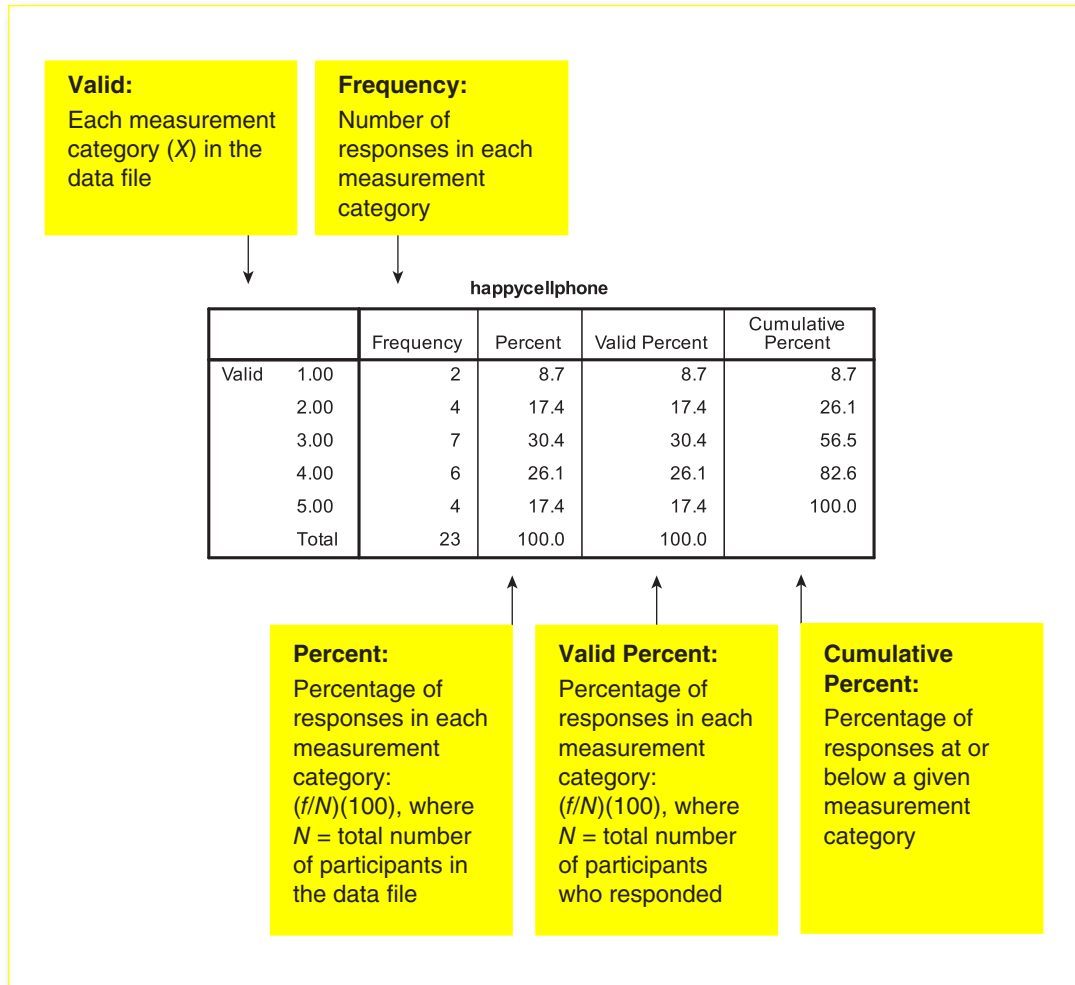
Reading Question

43. How many people responded with a 3 to the question, “I am very happy with my cell phone provider?”
- 2
 - 4
 - 7

Reading Question

44. What percentage of the respondents answered the question with a response of 4?
- 30.4
 - 26.1
 - 17.4

Figure 1.11 Annotated SPSS Frequency Table Output

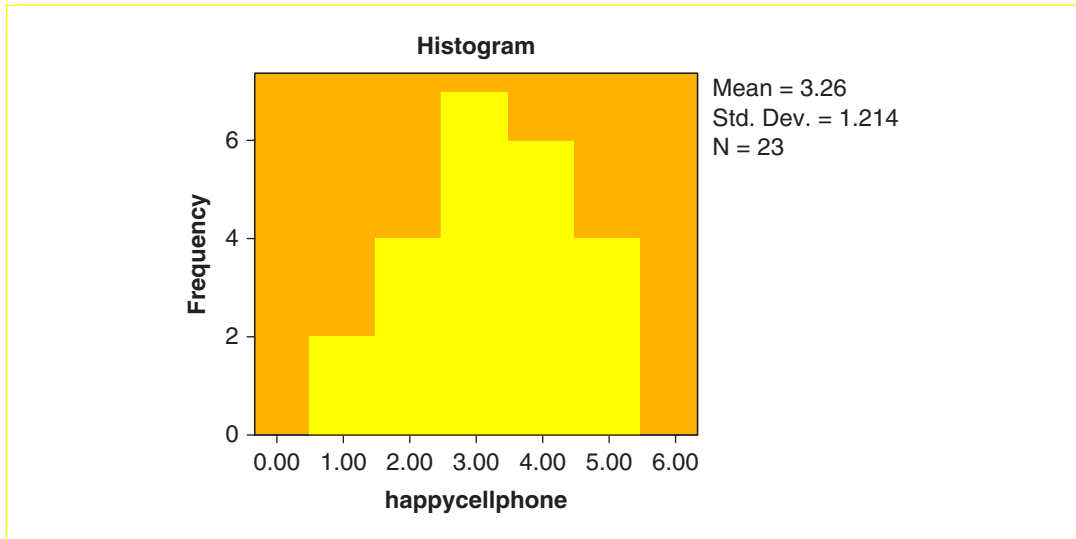


Reading Question

45. What percentage of the respondents answered the question with a response of 4 or a lower value?
- 56.5
 - 82.6
 - 100

Use the histogram in Figure 1.12 to answer the following two questions.

Figure 1.12 Frequency Histogram of “I Am Very Happy With My Cell Phone Service Provider” Data



**Reading
Question**

46. What is the most common response in the data?
- 2
 - 3
 - 4
 - 5

**Reading
Question**

47. How many people responded with the most common response?
- 7
 - 6
 - 5
 - 4

SPSS is a great tool for creating graphs to help you gain a better understanding of your data. However, it is not necessarily intended for creating presentation-quality graphs. You can customize graphs in SPSS by double clicking on the graph once you create it and then, once the image is open, double click on any aspect of the graph to change it. This is trickier than it sounds because there are a lot of options. We are not going to work on editing graphs in this book, but if you would like to edit graphs, you can use the help menu in SPSS to obtain further information. There are several other ways to create more advanced graphs in SPSS. You can explore these options by clicking on “Graphs” menu.

**Reading
Question**

48. It is possible to change the appearance of graphs created by SPSS.
- True
 - False

OVERVIEW OF THE ACTIVITY

In Activity 1.1, you will practice using the concepts introduced in this chapter, including samples, descriptive statistics, inferential statistics, populations, parameters, and sampling error. You will create frequency distribution tables by hand and using SPSS. When interpreting these tables, you will also learn about percentiles and how they can be obtained from a frequency distribution table. You will also create graphs by hand and using SPSS and describe their skew and kurtosis using the correct terminology. Finally, you will read research scenarios and determine what scale of measurement best describes the variables in the study.

Activity 1.1: Frequency Distributions

After reading the chapter and completing this activity, you should be able to do the following:

- Use common statistical terms correctly in a statistical context
- Construct a frequency distribution table from a bar graph
- Interpret data from a frequency distribution
- Use SPSS to create a frequency table
- Sketch a frequency distribution
- Identify distributions that are bell shaped, positively skewed, negatively skewed, leptokurtic, and platykurtic
- Identify nominal, ordinal, and interval/ratio variables in research scenarios
- Identify discrete and continuous variables in research scenarios

THERAPEUTIC TOUCH

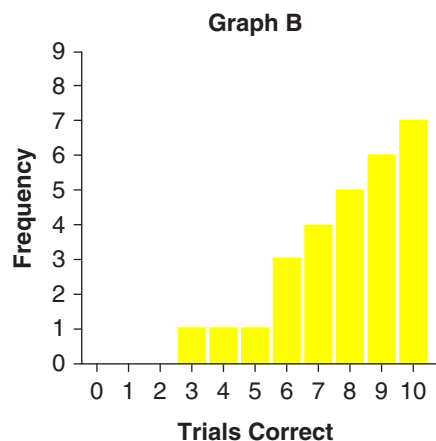
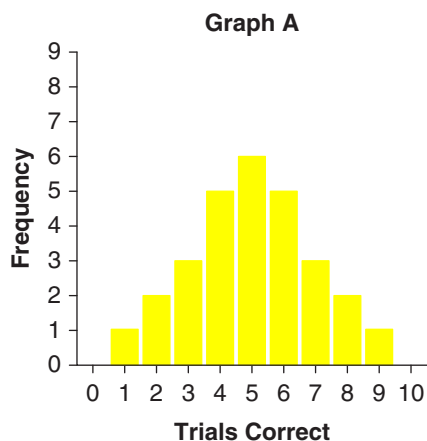
There is quite a bit of evidence that human touch is beneficial to our psychological and physical health. Hugs are associated with lower blood pressure, skin-to-skin contact can help preterm infants gain weight, and touch can improve immune system functioning (e.g., Field, 2010). Although there is little doubt of the benefits of physical touch, a treatment known as “therapeutic touch” (TT) is far more controversial. Therapeutic touch involves no actual physical contact. Instead, practitioners use their hands to move “human energy fields” (HEFs) in an attempt to promote healing. Proponents of this approach claim that it can help with relaxation, reduce pain, and improve the immune system.

Emily Rosa (who was just 9 years old at the time) and her colleagues (including her parents) investigated the basis of these TT claims by putting a sample of actual TT practitioners to the test (Rosa, Rosa, Sarner, & Barrett, 1998). In their study, Rosa and colleagues designed a method to determine if TT practitioners could actually detect HEFs. As the figure to the right illustrates, individual practitioners sat at a table facing a large divider that prevented them from seeing their own hands or Emily. The practitioners placed both of their hands through the divider on the table, palms up. Practitioners were told to indicate whether Emily was holding her hand above their right or left hand. Emily began each trial by flipping a coin to determine where to place her hand. She then placed her hand 8 to 10 cm above one of the practitioner's hands. The practitioners had to "sense" the HEF allegedly emanating from Emily's hand to determine if Emily's hand was over their right hand or left hand. Each practitioner went through a total of 10 of these trials.



If the TT practitioners can actually sense HEFs, they should be able to choose the correct hand far better than chance (i.e., 5 out of 10 times). However, if they really can't detect HEFs and the practitioners were really guessing, you would expect them to choose the correct hand *an average* of 5 out of 10 times. Some may get more than 5 correct and others may get less than 5 correct, but the most common number of correct answers would be about 5 of 10, *if the practitioners were guessing*.

1. Which of the following graphs represents the results you would expect *if the practitioners were guessing*? Explain your answer.



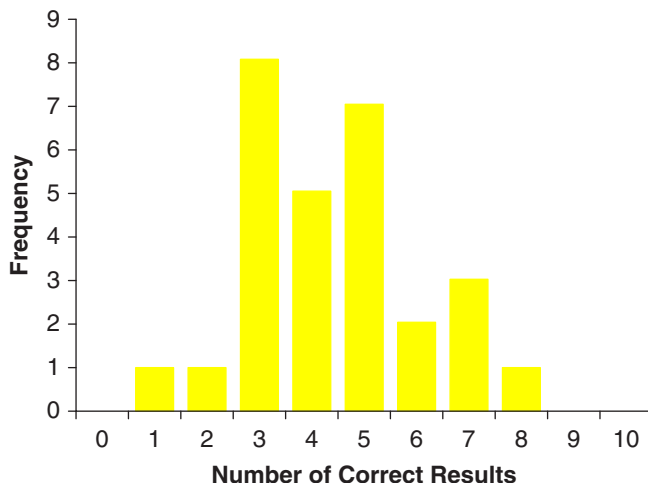
2. As mentioned previously, the researchers had a sample of TT practitioners participate in the experiment described earlier. They used the results from this sample to infer what the results would be if they had collected data from the entire population of TT practitioners. The purpose of their study was
- descriptive.
 - inferential.
3. Use three of the following terms to fill in the blanks: parameters, statistics, inferential, descriptive, sampling error.

If the sample of TT practitioners represented the population of TT practitioners well, the sample _____ would be similar to the population _____ and the study would have a relatively small amount of _____.

4. After the experiment was complete, the researchers counted the number of correct responses out of the 10 possible that were generated by each participant. The number of correct responses ranged between a low of 1 correct to a high of 8 correct. The variable “number of correct responses out of 10 trials” is measured on which scale of measurement?
- Nominal
 - Ordinal
 - Interval/ratio
5. Is the number of correct responses out of 10 a continuous or a discrete variable?
- Continuous
 - Discrete

The following bar graph is an accurate re-creation of the actual data from the experiment. The graph is a frequency distribution of the number of correct responses generated by each practitioner out of 10 trials. Use these data to answer the following questions:

6. Create a frequency distribution table based on the graph.



x	y

7. How many practitioners were in the sample?
 - a. 8
 - b. 10
 - c. 28
8. How many practitioners did *better* than chance (i.e., did better than 5 correct out of 10)?
 - a. 3
 - b. 6
 - c. 13
9. What *percentage* of the practitioners performed *at or below* chance?
 - a. 100
 - b. 78.6
 - c. 53.6
10. Do the data support the conclusion that TT practitioners can detect HEFs or do the data support the conclusion that they cannot and instead are guessing?
 - a. Yes, many of the practitioners performed above chance level. Although the other practitioners could not detect the HEFs, the people who scored above chance could detect HEFs.
 - b. No, most practitioners performed at or below chance levels. This suggests that, generally, the TT practitioners were not able to detect the HEFs.
11. Some of the TT practitioners were correct on 6, 7, or 8 of the trials. What should the researchers do next?
 - a. Conclude that these four individuals really can detect HEFs and encourage them to continue using TT to treat people.
 - b. Do the study again with the same people and see if they can replicate their above-chance performance.

GENERAL SOCIAL SURVEY

Every 2 years, the National Opinion Research Center asks a random sample of adults in the United States to complete the **General Social Survey** (GSS). All of the GSS data are available at www.norc.umd.edu. You will be using a small portion of the GSS that we placed in a file titled "gss2010.sav." You can access this file on the textbook website (<http://www.sagepub.com/carlson/study/resources.htm>). Load this file into SPSS.

Part of the GSS assesses respondents' science knowledge. In 2010, respondents answered questions from a variety of different sciences, such as "True or False. Antibiotics kill viruses as well as bacteria" and "True or False. Lasers work by focusing sound waves." For this assignment, we created the variable "ScientificKnowledge" by summing the total number of correct answers each participant gave to 10 science questions. The resulting "ScientificKnowledge" variable was measured on a ratio scale and had a possible range of 0 to 10 correct answers.

Use SPSS to create a frequency distribution table and graph of "ScientificKnowledge" scores. To create a frequency distribution table and graph, do the following:

- From the Data View screen, click on Analyze, Descriptive Statistics, and then Frequencies.
- Move the variable(s) of interest into the Variable(s) box. In this case, you will move "ScientificKnowledge" into the Variable(s) box.