STATISTICS AND DATA INTERPRETATION FOR SOCIAL WORK
James Rosenthal has taught at the Anne and Henry Zarrow School of Social Work at the University of Oklahoma, Norman, since 1985. His primary teaching areas have been in research methods and statistics. He has written two books, *Special Needs Adoption: A Follow-up Study of Intact Families* (1992 with Victor Groza) and *Statistics and Data Interpretation for the Helping Professions* (2001). He has written more than 40 journal articles and book chapters, primarily in the area of child welfare services (adoption, foster care, child maltreatment, children’s mental health). He has published in leading social work journals including *Children and Youth Services Review*, *Social Service Review*, *Social Work*, *Child Abuse and Neglect*, and *Child Welfare*. His master’s in social service administration is from the University of Chicago (1977) and his doctorate in research and evaluation methods is from the School of Education at the University of Colorado, Boulder (1984).

Jim lives in Norman, Oklahoma, with his wife, Cindy. He enjoys hiking, baseball, golf, and his dogs, Lenny and Sandy. He has two children, Catie and Aaron.
STATISTICS AND DATA INTERPRETATION FOR SOCIAL WORK

James A. Rosenthal, PhD
CONTENTS

Preface xv
Acknowledgments xvii

PART I: INTRODUCTION AND DESCRIPTIVE STATISTICS

1. Introduction and Overview 3
   1.1 Chapter Overview 3
   1.2 Statistics and Social Work 3
   1.3 Science and Research 4
   1.4 Variables and Measurement 4
   1.5 Samples and Populations 5
   1.6 Descriptive and Inferential Statistics 6
   1.7 Univariate, Bivariate, and Multivariate Statistics 6
   1.8 Random Assignment 8
   1.9 Levels of Measurement 9
      1.9.1 Basics 9
      1.9.2 Fine Points 10
   1.10 Chapter Summary 11
   1.11 Problems and Questions 12

2. Data Presentation 19
   2.1 Chapter Overview 19
   2.2 Frequency Distributions and Tables 19
   2.3 Figures 21
   2.4 Chapter Summary 24
   2.5 Problems and Questions 25

3. Central Tendency 29
   3.1 Chapter Overview 29
   3.2 Key Concepts in Univariate Descriptive Statistics 29
   3.3 Three Key Measures of Central Tendency 29
   3.4 The Mode 30
   3.5 The Median 30
   3.6 The Mean 31
3.7 Choosing Between Measures 32
3.8 Chapter Summary 33
3.9 Problems and Questions 34

4. Measures of Variability 39
4.1 Chapter Overview 39
4.2 The Concept of Variability 39
4.3 Assessing the Variability of Categorical Variables 40
4.4 The Range 41
4.5 The Interquartile Range 41
4.6 The Mean Deviation 41
4.7 The Standard Deviation 42
4.8 The Variance 44
4.9 Chapter Summary 45
4.10 Problems and Questions 45

5. Shape of Distribution 51
5.1 Chapter Overview 51
5.2 The Normal Distribution 51
5.3 Skewed Distributions 53
5.3.1 Characteristics 53
5.3.2 Skewness and Measures of Central Tendency 55
5.4 Kurtosis 57
5.5 Uniform and Bimodal Distributions 58
5.6 Percentages and the Normal Distribution 58
5.7 Introduction to z Scores 61
5.7.1 z Score Calculation 61
5.7.2 Basics of z Scores 61
5.7.3 Uses of z Scores 62
5.8 z Scores and the Normal Distribution 63
5.8.1 Problems About Percentages of Cases 63
5.8.2 Reminders and Cautions 65
5.9 Chapter Summary 66
5.10 Problems and Questions 67

6. The Concept of Relationship and Relationship Between Categorical Variables 75
6.1 Chapter Overview 75
6.2 Definition of Relationship 75
6.3 Comments on Relationship 76
6.4 Contingency Tables and Categorical Variables 77
6.4.1 Reading a Contingency (Crosstabs) Table 77
6.4.2 Assessing Relationship Using a Contingency Table 78
6.5 Size of Association 80
6.6 Difference in Percentages (D%) 80
6.7 Qualitative Descriptors of Size of Association 81
6.8 Risk Ratio (RR) 82
6.9 Difference in Percentages or Risk Ratio? 84
6.10 Chapter Summary 84
6.11 Problems and Questions 85
11. Controlling for Confounding Variables 143
   11.1 Chapter Overview 143
   11.2 Controlling for a Variable 143
       11.2.1 Basic Concepts 143
       11.2.2 Different Patterns Following Control 145
       11.2.3 Initial Relationship Persists 145
       11.2.4 Initial Relationship Weakens 146
       11.2.5 Initial Relationship Disappears 146
   11.3 Causal Models and Additional Considerations 147
   11.4 Control for Multiple Variables and Causality 149
   11.5 Interaction Effects 150
   11.6 Chapter Summary 151
   11.7 Problems and Questions 152

PART II: INFERENTIAL STATISTICS AND DATA INTERPRETATION

12. An Introduction to Inferential Statistics 161
   12.1 Chapter Overview 161
   12.2 Descriptive Versus Inferential Statistics 161
   12.3 Characteristics of Random Samples 161
   12.4 The Advantage of Random Samples 163
   12.5 Statistics and Parameters 164
   12.6 Characteristics of Estimators 165
   12.7 Sampling Error and Sampling Distributions 166
       12.7.1 Concepts 166
       12.7.2 Sampling Distribution of the Mean 168
   12.8 Sample Size and the Sampling Distribution of \( \bar{X} \) 170
   12.9 Chapter Summary 172
   12.10 Problems and Questions 173

13. Confidence Intervals for Means and Proportions 179
   13.1 Chapter Overview 179
   13.2 What Is a Confidence Interval? 179
   13.3 Confidence Intervals for Means 179
       13.3.1 Theory 179
       13.3.2 Formulas and Computation 181
   13.4 Confidence Intervals for Proportions and Percentages 184
       13.4.1 Theory 184
       13.4.2 Formulas and Application 185
   13.5 Five More Things to Know 187
   13.6 Chapter Summary 188
   13.7 Problems and Questions 189

14. The Logic of Statistical Significance Tests 195
   14.1 Chapter Overview 195
   14.2 Introduction to Significance Testing 195
   14.3 Probability 195
       14.3.1 Definition and Formula 195
       14.3.2 Probability and the Normal Distribution 196
   14.4 Null and Alternative Hypotheses 196
Contents

16.5 Factors Other Than Sample Size That Influence Power 252
  16.5.1 Overview 252
  16.5.2 Size of Relationship or Difference in the Population 252
  16.5.3 Reduced Variability of Independent or Dependent Variable 254
  16.5.4 Control for Third Variables 255
  16.5.5 Significance Level 256
  16.5.6 Directional Hypotheses and One-Tailed Tests 256
  16.5.7 Statistical Significance Test 257

16.6 How Much Power is Enough? 257

16.7 How Large Should Sample Size Be? 257

16.8 Nonrandom Samples and Significance Tests 260

16.9 Reporting Statistical Significance 260

16.10 What Statistical Significance Is (And Is Not) 261

16.11 Chapter Summary 261

16.12 Problems and Questions 263

17. The t Distribution and One-Sample Procedures for Means 269
  17.1 Chapter Overview 269
  17.2 Small Sample Size and Distributions 269
  17.3 Degrees of Freedom 269
  17.4 The Family of t Distributions 270
  17.5 Confidence Intervals for Means for Small Samples (and Large) 271
  17.6 Introduction to the One-Sample t Test 273
    17.6.1 Assumptions, Hypothesis Pairs, and Formula 273
    17.6.2 Decision Rules 274
  17.7 Carrying Out the One-Sample t Test 274
  17.8 Chapter Summary 277
  17.9 Problems and Questions 278

18. Independent Samples t Test and Dependent Samples t Test 283
  18.1 Chapter Overview 283
  18.2 Introduction to the Independent Samples t Test 283
    18.2.1 Purpose and Sampling Distribution 283
    18.2.2 Hypothesis Pairs 283
    18.2.3 Assumptions and Formulas 284
  18.3 Carrying Out the Independent Samples t Test Using the SPSS Software Package 285
  18.4 The Independence Assumption 287
  18.5 The Dependent Samples t Test 288
    18.5.1 Dependent Samples and Statistical Power 288
    18.5.2 Requirements 288
    18.5.3 Example Demonstrating Increase in Power from Positive Correlation 289
  18.6 Chapter Summary 289
  18.7 Problems and Questions 290

19. One-Sample Tests of Proportions 295
  19.1 Chapter Overview 295
  19.2 One-Sample Test of a Proportion 295
    19.2.1 Introduction 295
    19.2.2 Theory and Basics 295
    19.2.3 Carrying Out the Behavior Problems Example 296
22. More Significance Tests and Reasoning with Test Results 337
   22.1 Chapter Overview 337
   22.2 Statistical Significance Test of Pearson’s r 337
       22.2.1 Basic Logic 337
       22.2.2 Assumptions and Levels of Measurement 337
       22.2.3 Hypothesis Pair 338
       22.2.4 Decision Rules and Degrees of Freedom 338
       22.2.5 Carrying Out the Hypothesis Testing Model 338
       22.2.6 A Look at the Sampling Distribution of r 340
   22.3 A Correlation Matrix 340
   22.4 Comments on Hypothesis Testing and Confidence Intervals 343
       22.4.1 Hypothesis Testing 343
       22.4.2 Confidence Intervals 343
   22.5 Parametric and Nonparametric Tests 343
   22.6 Selected Parametric Tests 345
       22.6.1 Significance Test of Spearman’s r 345
       22.6.2 Tests of Association Between Two Ordinal-Level Categorical Variables 345
       22.6.3 Tests for Independent Samples 345
       22.6.4 Tests for Dependent Samples 345
   22.7 Parametric or Nonparametric Test? 346
   22.8 Data Transformation 347
   22.9 Single-Case Designs 349
       22.9.1 Basic Applications 349
       22.9.2 Comments on Single-Case Designs 351
       22.9.3 Serial Dependency 351
   22.10 Qualitative Methods and Statistics 352
   22.11 Reasoning with Data: A Brief Review 354
   22.12 Chapter Summary 356
   22.13 Problems and Questions 357

23. An Overview of Selected Multivariate Procedures 365
   23.1 Chapter Overview 365
   23.2 Multiple Regression Analysis 365
       23.2.1 Equation and Introduction 365
       23.2.2 Assumptions of Multiple Regression 368
   23.3 Advantages of Multivariate Analyses 370
   23.4 Logistic Regression 374
   23.5 Factorial Analysis of Variance 375
   23.6 Multivariate Procedures Related to Analysis of Variance 378
   23.7 A Glimpse at Selected Procedures 379
   23.8 Chapter Summary 380
   23.9 Problems and Questions 381

24. Generalizability, Importance, and a Data Interpretation Model 387
   24.1 Chapter Overview 387
   24.2 Generalizability 387
       24.2.1 Inferential Statistics and Generalizability 387
       24.2.2 Generalization Using Nonstatistical Tools 390
   24.3 Importance 392
   24.4 The Balanced Model for Data Interpretation 393
   24.5 Chapter Summary 395
   24.6 Problems and Questions 396
Appendix A Tables  401
A.1 Percentage of Cases in Selected Areas of the Normal Distribution  401
A.2 Critical Values for the t Distribution and Values for Confidence Intervals  403
A.3 Critical Values (Frequencies) for the Binomial Distribution:
   One-Tailed Test, Alpha = .05  404
A.4 Critical Values for the Chi-Square Distribution  405
A.5 Critical Values for the F Distribution  406
A.6 Critical Values for Pearson’s r  407

Appendix B Review of Basic Math  409
B.1 Basic Operations, Terms, and Symbols  409
B.2 More Symbols  409
B.3 Order of Operations  410
B.4 Positive and Negative Numbers and Absolute Values  410
B.5 Squares and Square Roots  411
B.6 Fractions  411
B.7 Algebra  412
B.8 Ratios, Proportions, Percentages, and Percentiles  413
B.9 Rounding  413
B.10 Math Review Problems  413
B.11 Math Review Answers  414

Appendix C Appropriate Measures for Different Situations  415
C.1 Selected Univariate Measures and Measures of Association  416
C.2 Selected Statistical Significance Tests for Univariate, Bivariate, and Multivariate Situations  417

Appendix D Symbols in the Text  419

Appendix E Formulas in the Text  421

Appendix F Answers To End-Of-Chapter Problems and Questions  425

Notes  453
References  467
Index  469
OVERVIEW

Statistics and Data Interpretation for Social Work differs from most statistics texts in several key ways:

- It provides pragmatic examples in real-world settings and situations.
- It emphasizes that data assessment builds on but is not limited to statistics.
- It builds strong links to research methods courses, in particular demonstrating how social workers
  - assess whether study results reflect the effects of programs and interventions rather than extraneous factors (bias);
  - assess the applicability of research findings to the practice and policy situations in which they work; and
  - assess the importance (practical significance) of statistical results for clients and communities.

This text is a thorough rewrite of Statistics and Data Interpretation for the Helping Professions (2001). It presents less theory and more examples than did its predecessor. Even so, it is not a “baby statistics” text, one that is watered down and that avoids key (and sometimes difficult) concepts. If not a baby text, it is an introductory one; it provides the fundamentals for carrying out straightforward statistical analyses in basic research designs. It emphasizes concepts and skills much more than math and formulas. Scanning the text, the reader will observe the many problems and questions at the end of each chapter—indeed, 140 pages are devoted to problems and questions. These provide considerable opportunity to put the text’s content into practice. The text works well in a stand-alone statistics course or in a research methods course in which statistics is a major content area. It is appropriate at both undergraduate and graduate levels. Although designed for social work students, it will work well in related professions such as human relations, counseling, criminology, sociology, and public administration.

The text is accompanied by a 200-plus page online companion guide for the IBM SPSS statistical software program. This companion introduces SPSS and then gears SPSS exercises to particular chapters in the text. It is (to my knowledge) the most visual SPSS guide available. It is

---

This book tries to minimize the use of gender-related pronouns. When such usage is necessary, it uses feminine pronouns because most social workers are women.
filled with screen shots (large and small) that walk the reader through key steps of data analysis with SPSS. Although designed for use with Statistics and Data Interpretation for Social Work, the companion stands well on its own as a basic SPSS primer.

CONTENTS

The text’s first chapter emphasizes that the profession of social work seeks to build its interventions on scientific knowledge—this is evidence-based practice. The second chapter involves data presentation, both with tables and figures (graphics). The next six chapters focus on descriptive statistics, tools for describing the data in one’s sample. Some of the key topics covered here include measures of central tendency (i.e., the mean), measures of variability (i.e., the standard deviation), distributions (normal distribution, skewed distributions, z scores), and measures of association (difference in percentages, odds ratio, correlation, standardized mean difference). Chapters 6–9 direct considerable attention to size of relationship (effect size), that is, to how researchers assess whether observed relationships and differences are “large” or “small.” Chapters 10 and 11 focus on how researchers determine whether one variable (say, for instance, a behavior modification intervention) actually causes another (say, a child’s school behavior).

The text’s second (and longer) half presents inferential statistics, tools for drawing conclusions about populations that are larger than one’s sample. Chapters 12 and 13 deal with confidence intervals (much like the margins of error presented in newscasts for political polls). Chapters 14–16 present the logic behind statistical significance tests—how a researcher decides whether a difference or relationship may just be due to the luck of the draw (to chance). Chapters 17–22 present a wide array of statistical significance tests for use in many different situations. These include t tests, chi-square tests, analysis of variance (ANOVA), and tests for small samples and single-case designs. Chapter 23 enters the realm of multivariate statistics and presents multiple regression, logistic regression, factorial ANOVA, and other selected tests. The final chapter integrates the book’s content and focuses on the qualitative (nonstatistical) aspects of data interpretation.

SUMMING UP

Statistics and Data Interpretation for Social Work provides a solid introduction to statistics and data analysis. It has abundant problems on which students can test their knowledge. The 200-page plus online SPSS guide is filled with screenshots that guide students visually through the steps of data analysis. The text has strong, purposive links to research methods and to social work practice. It emphasizes reasoning. This reasoning begins with statistics, but moves beyond towards more comprehensive assessment that can guide social work practice. The strong foundation in statistics and data interpretation can help you (the student) as you begin to help people and the communities in which they live.
My great thanks go to my family: Cindy, Catie, and Aaron (and also Charlie, Don, and Lee, and Mom and Dad). And I should also mention great canine companionship: Chip, Monza, Hogan, Rainbow, Koal, Mui-Mui, and now, Lenny and Sandy. All deserve medals (or bones) for putting up with me and my bad jokes.

I have had and still have wonderful colleagues at the Anne and Henry Zarrow School of Social Work. Rather than taking a chance on missing someone, I say, simply, many thanks to all.

Thanks to Jennifer Perillo at Springer who encouraged me to begin this project and to Sheri W. Sussman and Michael O’Connor who, with the able assistance of Jessica Jonas at Absolute Service Inc., helped bring it “home.”

This text states that there is no such thing as a normal distribution in the real world. I am blessed to have had a truly abnormal distribution of family, friends, and experiences both in growing up and—this presumed to have occurred by now—continuing onward.

James Rosenthal
Norman, OK
October 2011
Part 1

INTRODUCTION AND DESCRIPTIVE STATISTICS

Part 1 begins by introducing concepts and terms to give you a solid footing in the field of statistics. Next, it discusses how to present data. Its major focus is on descriptive statistics, the tools that researchers use to describe and summarize data. Chapters 3, 4, and 5 present tools for describing a single variable. Some examples of variables (things that vary) include height, political party affiliation, and whether one is employed (yes or no). Among the most important tools for describing single variables are the mean, the median, and the standard deviation. Chapters 6–9 present tools for assessing the relationship between variables. For instance, amount of time studying for a test and grade earned on that test have a relationship because (in most cases) those who study longer earn higher grades. One of the most important tools for assessing relationship is the correlation coefficient \( r \). Finally, Chapters 10 and 11 shift the focus away from relationship per se to how researchers determine whether one variable in a relationship actually causes (affects) the other.
1.1 ■ CHAPTER OVERVIEW

Social work strives to develop evidenced-based practice, practice grounded in scientific knowledge. Chapter 1 begins with examples that demonstrate how statistics contributes to this endeavor. Next, it discusses the basics of science and research. It introduces variables and contrasts categorical and numeric variables. As it moves along, it overviews key topics covered in this book. It distinguishes between samples and populations and between random and nonrandom samples. It presents the two major branches of statistics—descriptive statistics and inferential statistics—and contrasts univariate, bivariate, and multivariate statistical procedures. It discusses relationships among variables and sketches how researchers draw conclusions about whether one variable causes another. Random assignment is important in this endeavor. The chapter provides a glimpse on how statistical significance tests examine the role of luck (chance) in study results. It closes with discussion of the four levels of measurement: nominal, ordinal, interval, and ratio. These provide guidance on which procedures to use in different situations.

1.2 ■ STATISTICS AND SOCIAL WORK

“Social work is a profession . . . committed to the pursuit of social change, to quality of life, and to the development of the full potential of each individual, group, and community in a society” (Wikipedia, 2010a). Statistics is “the science of making effective use of numerical data” (Wikipedia, 2010b). Why do social workers need statistics?

Social workers need to learn what “works” and what does not. A couple of examples can make this point. Fisher, Gunnar, Dozier, Bruce, and Pears (2006) developed a therapeutic intervention to help foster parents better meet the emotional and behavioral needs of preschool children in their care. Preliminary study results suggest that this intervention promotes capacity for attachment in foster children and, for some children, actually increases levels of the hormone cortisol. Because cortisol is involved in the regulation of stress, this suggests that the intervention may help children handle stress more effectively. A second example: Social workers have long been concerned about possible long-term negative impacts of foster care. A recent study compared young adult outcomes—high school graduation, public assistance use, criminal behavior, drug use, teenage pregnancy, and homelessness—for about 300 young adults who had spent time in foster care at some time during their childhood and about 9,000 who had never been in such care (Berzin, 2008, p. 181). Preliminary statistical analyses indeed found worse outcomes for those who had been in foster care. Yet, more sophisticated analyses suggested that these worse
outcomes were not caused primarily by foster care experiences but rather by a host of factors that those who had experienced foster care had been exposed to prior to entering care. These factors included poverty, having a very young birth mother, and a birth family environment with less opportunity for learning and socialization.

The two just-discussed studies are part of a growing knowledge base for effective social work practice in foster care. This knowledge is grounded in science. Expanding our focus from foster care to social work as a whole, the increased grounding of social work practice in scientific knowledge is one of the most important trends in the field over the past 30 or so years. Social work practice based on the “best scientific evidence available” is termed evidence-based practice (Rubin, 2010, p. 315). The effective use of statistics is essential in this endeavor.

The two studies mentioned earlier were both large ones, involving many participants. Yet, statistics is also important in work with individual clients. For instance, you will need ways to assess whether your clients are making effective progress toward their treatment goals.

I would be lying to tell you that statistics is easy. But, on the other hand, introductory statistics is not so difficult. It is much more about key ideas than complicated math. This text emphasizes interpretation more than calculation. I want you to understand the conclusions that can—and cannot—be drawn in different situations.

So let us get started building statistical tools for social work practice. You will need to know what works and what does not.

1.3 SCIENCE AND RESEARCH

Science comprises “systematic knowledge gained through observation and experimentation” (Random House Webster’s Dictionary, 1987, p. 1716). It has two sides: a theoretical side based on theory, concepts, and ideas; and an applied side built on real-world observations. The theoretical side is termed theory. The gathering of real-world observations (i.e., data) is termed research.

Social science research uses two basic methods, quantitative and qualitative. Quantitative research methods are characterized by objective measurement, which is the assigning of numbers or classifications to observations. Both of the just-discussed foster care studies used quantitative methods. Qualitative research methods “emphasize depth of understanding and the deeper meanings of human experience” (Rubin & Babbie, 2008, p. 643). An example might be in-depth interviews of persons who grew up in poverty, experiencing multiple risks and stressors, who, nevertheless, experienced success as adults. These interviews would probe for the particular perspective of each person and would not include questions that could be answered by checking a box such as “yes” or “no” or, say, “strongly agree.” Checking responses in boxes is a quantitative method.

Social work research is, almost without exception, applied research—research focused on real-world problems. This contrasts with pure research, research that seeks to build knowledge for its own sake. Much research in social work is program evaluation, research carried out to judge the usefulness of a social program or intervention.

1.4 VARIABLES AND MEASUREMENT

Each unit on which measurements are recorded is a case. In social work research, cases are typically individual people. For instance, if you distribute a questionnaire to the students in your statistics or research class, each student is a different case. But cases are not always individuals. If you study child abuse rates in the 50 different states, then each state is a different case.
Variables are the “ingredients” of data, the different things that are measured. So, if you measure the gender, height, and academic major of each student in your class, each of these is a different variable.

The just-provided definition of variable is a general one. There is also a more specific definition: A variable is something with more than one value. For instance, gender takes on the values, female and male. Height can assume many different values, say, 5 ft. 4 ½ in., 5 ft. 7 in., 6 ft. 2 ¼ in., and so on. Before going further, let us define value: Value(s) (attributes) are the different numbers or classifications that a variable assumes.

We may contrast a variable with a constant, something that takes on only one value. For instance, the number “2” is a constant. If all cases have the same value on a given “variable,” (here, we use the general definition) then that “variable” is not actually a variable but is, instead, (using our more specific definition) a constant. For instance, if all persons in a study are female, then sex is a constant rather than a variable.

Variables may be either categorical or numeric. Categorical variables (qualitative variables) have nonnumeric values. For instance, sex is a categorical variable because its values (female, male) are nonnumeric. Eye color (brown, blue, hazel, green, gray, etc.) is another example of a categorical variable. A categorical variable with exactly two values—for instance, sex has the values female and male—is a dichotomous variable (binary variable). Numeric variables (quantitative variables) have numeric values. Height, as measured in the previous example is numeric. On the other hand, if persons categorized their height as “short,” “medium,” or “tall,” then height measured in this way is categorical. How many cars (0, 1, 2, 3, 4, etc.) that a family owns is a numeric variable, as is, for instance, the percentage correct that you earned on your most recent test (83, 91, 88, etc.). Values of numeric variables are often termed scores.

1.5 ■ SAMPLES AND POPULATIONS

A population consists of all of the objects that possess a specified set of characteristics. For instance, if there are 30 students in a class, these 30 students are the population of students in the class.

A sample consists of some but not all of the objects in a population. For instance, the students enrolled in, say, one or more social work courses this semester are a sample of students at your college; they are some of the students at the college. And, for instance, the students who sit in the front row in a given class are a sample of students in that class.

Random samples (probability samples) are selected by methods of chance (picking names out of hat, a computer program selects names at random, etc.). When methods of chance are not used, the sample is a nonrandom sample (nonprobability sample). So, if your professor picks from a hat the names of 10 students who will participate in a special class exercise, the selected students are a random sample of students in the class. On the other hand, if she asks for 10 volunteers, the volunteering students are a nonrandom sample of students in the class.

In addition to referring to “some but not all of the objects in a population,” the term sample has a second meaning in research. Sample is also used to refer to the participants in a research study. To reduce confusion, I typically refer to those selected to be in a research study as the study sample. So, if 100 persons fill out, for instance, a web-based survey, these persons are the study sample. In a general sense, sampling refers to the method used, random sampling (methods of chance used) or nonrandom sampling (methods of chance not used), to select participants for the study sample.
1.6 ■ DESCRIPTIVE AND INFERENTIAL STATISTICS

The field of statistics was defined previously as “the science of making effective use of numerical data” (Wikipedia, 2010b). A statistic is a numerical summary of data (Toothaker & Miller, 1996). For instance, if the average age of students in a class is 20 years old, then “20 years” is a statistic because it summarizes data pertaining to the class. And, by the same logic, if 80% of students respond that they like rock music, then “80%” is also a statistic.

Statistics has two major branches:

- **Descriptive statistics** (descriptive statistical procedures) describe the study sample.
- **Inferential statistics** (inferential statistical procedures) are used to draw conclusions about a population based on a random sample selected from that population.

So, suppose a professor reports the following: “The average age of students in my class is 20 years old and 80% of these students enjoy rock music.” The professor is simply describing the study sample—in particular, she is not drawing any conclusions that go beyond this sample. As such, the professor is engaging in descriptive statistics. Chapters 3–9 focus on descriptive statistics.

Now, suppose a researcher takes a random sample of students at a university and finds that 72% of persons in the study sample support a proposed change in immigration policy. Based on this sample (and using skills to be taught in Chapters 12 and 13), the researcher states, “I am 95% confident that the percentage of all students in the university who support the change is between 64% and 80%.” This example demonstrates inferential statistics as the researcher is drawing a conclusion about a population based on a sample randomly selected from that population.

Although an important exception will be discussed in Chapter 16, Section 8, formally speaking, inferential statistics may not be used with nonrandom samples. For instance, suppose that a social work professor finds that 90% of students in a social welfare policy class support proposed legislation to offer additional services to the homeless. Based on this sample, the professor may not use statistical procedures to draw a conclusion about the percentage of students at her university who support this legislation. She may not do so because the study sample is not a random sample of students at the university.

At the risk of oversimplifying with a random sample, only the “luck of the draw” causes differences between the characteristics and opinions of those in the sample and the characteristics and opinions of those in the population from which the sample was drawn. As such, inferential statistical procedures may be used. Chapter 12 presents more on how the “luck of the draw” operates and on when inferential statistics are used.

1.7 ■ UNIVARIATE, BIVARIATE, AND MULTIVARIATE STATISTICS

In addition to dividing the field of statistics into the two branches of descriptive and inferential statistics, we may classify statistical procedures as univariate, bivariate, or multivariate. These procedures may be used in either descriptive or inferential applications.

**Univariate statistics** pertain to a single variable at a time. For instance, it was reported earlier that 72% of students supported a change in immigration policy. As only a single variable (opinion on immigration policy) is involved, this is an example of univariate statistics. Chapters 3–5 present univariate descriptive statistics methods.

**Bivariate statistics** convey the relationship (or lack thereof) between two variables. Two variables are related (associated) when the values of one variable vary, differ, or change...
According to those of the other. For instance, sex and length of hair are related because (at least in most cultures) women have, on average, longer hair than do men. As another example of bivariate statistics, if a researcher writes "60% of Democrats but only 40% of Republicans voted for Legislation Z," she is engaging in bivariate statistics because she is communicating about a relationship between two variables, political party (Democratic or Republican) and vote on Legislation Z. (for the legislation vs. against it). In this example, because Democrats and Republicans vote differently, party affiliation and the vote on Z are related (associated).

The examples earlier involve variables that are related. If the same percentage of women and men respond that they like rock music—say, 80% of women and 80% of men like rock—then sex and liking rock music are unrelated (unassociated). Suppose that batting averages of left-handed hitters and right-handed hitters are the same (.283 for each group), then “batting handedness” (left vs. right) and batting average are unassociated. The idea here is that being a left-handed or right-handed batter does not tend to “go with” being a better (high average) or a worse (low average) hitter. Chapters 6–9 present bivariate, descriptive statistical methods.

As is discussed in depth beginning in Chapter 14, relationships in study samples can occur simply by luck (chance). For instance, suppose that in the full population of students at your university, the same percentage of women and men are vegetarians; for the sake of argument, suppose that this percentage is 10.7%. Thus, in this population, sex and being vegetarian are not related. Suppose that you draw a random sample of 25 women and 25 men for your study sample. Because of the luck of the draw, the percentages of vegetarians in your study sample will almost surely differ from the percentages in the population. Let us say that in your study sample, 12.4% of women and 9.8% of men are vegetarians. Hence, in your study sample, sex and being vegetarian are related (because the percentage of vegetarians differs). This is so, even though there is no relationship in the population.

Sometimes, relationships observed in study samples are caused only by the luck of the draw. Other times, researchers find relationships in study samples because the variables are actually related in the population. Trying to determine whether a relationship in a study sample reflects only luck or, instead, reflects an actual relationship in the population is a fundamental issue in inferential statistics. The key tool in this task is the statistical significance test. Statistical significance tests are used to determine whether study sample results are likely to be due to the luck of the draw. Most of the second half of the text covers significance tests.

Multivariate statistics involve three or more variables at a time. Multivariate statistics often concern whether one variable actually affects (i.e., causes) another. For instance, suppose that a study demonstrates a relationship between eating vegetables and longevity; those who eat more vegetables, on average, live longer. Perhaps this relationship is not a causal relationship (causal association), one in which one variable affects the other. Instead, it may be caused by a third variable. For instance, perhaps those who eat lots of vegetables exercise more intensely than those who eat less. This being so, the relationship between vegetables and longevity may not be due to the effects of vegetables but instead to those of exercise. In other words, those who eat more vegetables live longer not because they eat vegetables but because they exercise more. The third variables that bring about relationships between other variables, termed confounding variables (third variables), are discussed in Chapters 10 and 11.

Because we are discussing causality (what causes what), it is a good time to define two common terms, independent variable and dependent variable. An independent variable affects another variable. A dependent variable is affected by another variable. So, suppose that visiting persons who are in nursing homes reduces depression. In this example, because visiting does the “affecting” (the causing), it is the independent variable. Because depression is affected (caused), it is the dependent. Chapter 23 demonstrates that several independent variables can be entered simultaneously into a single equation to see which of these most affects a dependent variable. This is an example of multivariate statistics.
Returning to our discussion of independent and dependent, sometimes, two variables that are related cannot be classified easily as independent and dependent. For instance, how high persons can jump in the high jump and how far they can jump in the long jump are related. On average, persons who jump “high” tend to jump “long” and those who jump “low” tend to jump “short.” But it does not make sense to say that long jumping causes high jumping or that high jumping causes long jumping. So, in this case, there is no independent or dependent variable; the two variables are simply related.

1.8 RANDOM ASSIGNMENT

Prior to examining random assignment, some terms need to be introduced. A group consists of those who possess some characteristic. A treatment group consists of those who receive a particular intervention (treatment). An intervention (treatment) is, broadly speaking, the “things that are done” to the research participant or client. Examples of social work interventions include a behavior modification program for a child, marital therapy for a couple experiencing difficulty, parenting skills training for a new parent, or a community intervention for a community under stress.

Assignment refers to the method used to assign participants to groups. It is distinct from sampling, which pertains to how participants were selected to be in the study sample. Random assignment (randomization) is the use of methods of chance to assign participants to groups.

The following is an example of a study that uses random assignment: A statistics professor puts students’ names in a hat. She picks names randomly from the hat, assigning (at random) half to receive a software-based intervention to enhance statistics skills and half to have extra time with a teaching assistant. At the end of the semester, the professor compares scores on the final exam in the two groups.

An example of the same study but with a nonrandom assignment process is as follows: A statistics professor asks students which of the two interventions they want to sign up for: (a) the software-based intervention or (b) the teaching assistant. Students select an intervention and are assigned to it. At the end of the semester, the professor compares scores on the finals in the two groups.

Studies that use random assignment are termed randomized studies (randomized clinical trials). The great strength of the randomized study is that (at the risk of oversimplifying) the only thing that distinguishes treatment groups as the intervention begins is the luck of the draw of the assignment process. More precisely, confounding variables are not a concern. So, if a researcher sees a difference in outcomes between two treatment groups, that researcher knows that this difference is caused by either (a) the luck of the draw of the assignment process or (b) the greater effectiveness of the intervention received in one group than of that received in the other. The researcher may conduct a significance test to see whether luck alone is a plausible explanation and, if it is not, may be confident that the results reflect the effects of the intervention.

Contrast this with a nonrandomized study. In a nonrandomized study, confounding variables cannot be ruled out as an explanation for study results. So, if a researcher sees a difference in outcomes between the two groups, that difference may be caused by (a) the luck of the draw of the assignment process, (b) the greater effectiveness of the intervention received in one group than of that received in the other, or (c) a confounding variable(s). Consider, for instance, the second version of the professor’s study, the one in which students choose their own group. Suppose that those instructed by the computer do better on the course finals than those instructed by the teaching assistant. Presume also that the difference is substantial enough so that the professor can be confident that it is not caused by luck. The problem is that the researcher will never know with confidence whether the result is caused by the greater effectiveness of the computer program over the teaching assistant or to a confounding variable(s).
What confounding variables might be at work? Well . . . for instance . . . relative to those who chose the teaching assistant, those who chose the computer program may have (a) been more motivated in the course, (b) had better math skills as the course began, and (c) had more time to study. The researcher will not be able to unravel whether one of these variables—or perhaps some other confounding variable not mentioned—or the greater effectiveness of the software package explains the better performance of the computer group on the statistics finals.

Suffice it to say that, in the absence of randomization, drawing conclusions about *causality*—that is, about what causes what—is a hazardous undertaking. On the other hand, with randomization, that researcher can, almost always, be confident that results that are larger than those that might be due to luck are indeed caused by the intervention. Chapters 10 and 11 discuss these issues in depth.

**1.9 LEVELS OF MEASUREMENT**

**1.9.1 Basics**

As discussed earlier, variables may be classified as categorical (qualitative) or numeric (quantitative). In addition, variables may be measured at four different *levels of measurement* (*scales of measurement*). These levels may be ordered from low to high. As one moves from lower to higher levels, greater precision is gained and new conclusions can be drawn. Ordered from low to high, the levels of measurement are nominal, ordinal, interval, and ratio. All categorical variables are at the nominal or ordinal level.

At the **nominal** level of measurement, one may *classify* a variable’s values into separate categories, but these categories may not be ordered. For instance, sex is measured at the nominal level. One may classify sex as female or male. However, these values may not be ordered (Female is not higher than male. Male is not higher than female.). Another example is eye color (brown, blue, hazel, or green). The values of eye color may be classified but not ordered. It makes no sense to ask, “Which is higher, brown, blue, hazel, or green?” This question asks for an ordering that is neither possible nor logical.

At the **ordinal** level of measurement, one may *classify and order* values. For instance, consider the responses on a class evaluation question excellent, good, fair, or poor. “Excellent” is higher than “good,” which is higher than “fair,” which is higher than “poor.” As such, the class evaluation question is at the ordinal level of measurement. Most questions probing agreement represent ordinal-level measurement. For instance, the responses strongly agree, agree, disagree, and strongly disagree may be ordered to convey level of agreement or disagreement.

At the ordinal level, the researcher may not measure the difference between values. For instance, one may not measure the difference between excellent and good. One knows that excellent is higher than good but does not know by how much. More formally, to find differences, one must be able to subtract one value from another value, but subtraction is not possible with nonnumeric values.

In **rank ordering**, objects are ordered on some characteristic from highest to lowest. The object’s position in that ordering is their **rank**. Rank orderings are at the ordinal level.

For instance, suppose that there are 37 students in your current class. We could order them from tallest to shortest and assign ranks to each—“1” to the tallest, “2” to the next tallest, and so on down to “37” to the shortest. We would then know, for instance, that the student assigned Rank 5 was taller than the student assigned Rank 6. Yet, we would not know the actual difference in height between any two ranks. For instance, we would not know how much taller Rank 5 was than Rank 6.
At the **interval level**, the researcher can order values and, in addition, can measure differences between values. Differences can be measured because the values of interval-level variables represent numeric quantities, and thus, subtraction is valid. Temperature in degrees Fahrenheit is an example of an interval-level variable. To find the difference between, say, 50 and 40 degrees, subtract: $50 - 40 = 10$.

Ratios cannot be interpreted meaningfully at the interval level of measurement. For instance, suppose that it is 8 °F one day and 4 °F the next day. Dividing 8 by 4 yields the ratio “2” ($8 / 4 = 2$ or 2 to 1). This ratio (falsely) conveys that there was twice the quantity of heat on the first day as on the second—obviously, this was not so. For a ratio to be valid and meaningful, the zero point on the measurement scale must be a *true zero*, one that conveys the absence of the quantity being measured. The zero point on the Fahrenheit scale is an *arbitrary zero*, and thus, ratios involving degrees Fahrenheit are not meaningful.

When the zero (0) on the measurement scale is a true zero, ratios are meaningful and, hence, measurement is at the **ratio level**. Variables at the ratio-level measurement are, on balance, more common than are those at the interval level. For instance, physical quantities such as height and weight are typically measured at the ratio level. Let us use weight as an example. If Fred weighs 200 lb, and Yi weighs 100 lb, dividing Fred’s weight by Yi’s ($200 / 100 = 2$ or 2 to 1) yields a valid and meaningful ratio. We may indeed conclude that Fred weighs twice as much as Yi. **Counts** are at the ratio level of measurement. For instance, if Professor X published nine articles and Professor Y published three articles, then Professor X published three times as many articles as Professor Y, $9 / 3 = 3$.

Observe that ratio-level measurement does not require that any case actually has the value “0.” For instance, no real person weighs 0.00 lb. The key idea is that zero on the measurement scale conveys the absence of the quantity being measured. This is so for weight; if something weighs “0.00” lb, it has no weight.

Different statistical procedures are used with variables at different levels of measurement. For instance, given nominal-level measurement, one procedure is likely appropriate. Given ordinal-level measurement, another may be indicated. An exception is that, at least in introductory statistics, the same statistical procedures are used for interval- and ratio-level variables. This being so, from this point forward, this text groups these levels into a single level—the **interval/ratio level**.

Because greater precision is gained at higher levels of measurement, it is generally advisable to measure at the highest possible level. As an example, do not simply obtain rank orderings of height (ordinal level) when you can measure using, say, a tape measure (interval/ratio level). A helpful tip: To remember the ordering of levels of measurement from low to high, think of the letters of the French word for night, “noir”: nominal, ordinal, interval, ratio.

It may be useful to relate the levels of measurement to the two types of variables: categorical and numeric. All variables at the nominal level are categorical. Most ordinal-level variables do indeed have categories and thus are categorical. Examples of categorical ordinal-level variables include those measuring, for instance, level of agreement (strongly disagree, disagree, agree, strongly agree), ratings (poor, fair, good, excellent), social class (lower, middle, upper), how often things happen (never, sometimes, often, always), and education level (less than high school, high school, college, graduate). Although at the ordinal level, rank orderings are numeric. However, remember that mathematical operations (for instance, calculating differences between values) are not valid with rank orderings. Finally, all variables at the interval/ratio level are numeric.

**1.9.2 Fine Points**

Sometimes, researchers assign numbers to the values of categorical variables as, for instance, *strongly agree* = 4, *agree* = 3, *disagree* = 2, and *strongly disagree* = 1. The assigning of numbers does not make the level of measurement interval/ratio. In particular, ordinal-level variables
remain ordinal-level variables whether numbers have been assigned. You should think of (and we will term) the numbers assigned to categories as codes rather than as numeric quantities.

A multi-item scale consists of multiple items, each of which probes some aspect of a concept. For instance, a multi-item self-esteem scale might consist of, say, 20 items, each probing some aspect of self-esteem. Examples might be “My opinions are valued,” “I take pride in what I do,” and so on. These items are almost always at the ordinal level of measurement. Researchers create scores on multi-item scales by summing codes for the items. For instance, for our self-esteem scale, the researcher would sum the codes for the 20 items.

The following question arises: What is the level of measurement of multi-item scale scores? Formally, these scores are not at the interval/ratio level. This is because summing together codes to derive a numeric score is not valid mathematically. Pragmatically, however, most researchers regard multi-item scores as being “almost” at the interval-ratio level. As such, they take the position that the statistical procedures designed for this level of measurement may be appropriately used to analyze them. I take this position in this text. I treat multi-item scale scores as interval-ratio level variables and use procedures appropriate for such variables with these scores.

1.10 CHAPTER SUMMARY

Statistics is “the science of making effective use of numerical data . . . ” (Wikipedia, 2010b). A solid understanding of introductory statistics is important for evidence-based practice, practice based on “the best scientific evidence available” (Rubin, 2010, p. 315).

Science comprises “systematic knowledge gained through observation and experimentation” (Random House Webster’s Dictionary, 1987, p. 1716). Its theoretical side is termed theory. The gathering of real-world observations is termed research. The observations gathered are data.

Quantitative research methods are characterized by objective measurement, which is the assigning of numbers or classifications to observations. Qualitative research methods “emphasize depth of understanding and the deeper meanings of human experience” (Rubin & Babbie, 2008, p. 643). Program evaluation is carried out to judge the usefulness of a social program or intervention.

Individual units are cases. Variables are the “ingredients of data.” A variable is something with more than one value. Value(s) are the different numbers or classifications that a variable takes on or assumes. A constant takes on only one value. Categorical variables (qualitative variables) have nonnumeric values. A categorical variable with exactly two values is a dichotomous variable. Numeric variables (quantitative variables) have numeric values.

A population consists of all of the objects that possess a specified set of characteristics. A sample consists of some but not all of the objects in a population. Random samples (probability samples) are selected by methods of chance. When methods of chance are not used, the sample is a nonrandom sample (nonprobability sample). Participants in a study form the study sample. In a general sense, sampling refers to the methods used to select the study sample.

A statistic is a numerical summary of data (Toothaker & Miller, 1996, p. 7). Descriptive statistics describe the study sample. Inferential statistics are used to draw conclusions about a population based on a random sample selected from that population. With a random sample, only the luck of the draw causes differences between the sample and the population from which the sample is drawn. Although an important exception is presented later, inferential statistics should not be used with nonrandom samples.

Univariate statistics pertain to a single variable at a time. Bivariate statistics convey the relationship (or lack thereof) between two variables. Two variables are related (associated) when the values of one variable vary, differ, or change according to those of the other. Relationships in study samples can occur simply by the luck of the draw. Statistical significance tests determine whether study sample results are likely to be due to the luck of the draw.
Multivariate statistics involve three or more variables at a time. In a causal relationship, one variable affects the other. Confounding variables are third variables that bring about relationships between other variables. An intervention (treatment) is the “things that are done” to the research participant.

Sampling refers to how participants were selected to be in the study sample. Assignment refers to how participants are assigned to groups. Random assignment (randomization) is the use of methods of chance to assign participants to groups. In a randomized study, the only thing that distinguishes groups as the intervention begins is the luck of the draw of the assignment process. Confounding variables are not a concern.

In a nonrandomized study, confounding variables can cause differences between groups. It can be difficult, if not impossible, to determine whether a difference is caused by a confounding variable(s) or by the effects of the intervention. In a randomized study, given that a difference is sufficiently substantial so that “luck” alone is an unlikely explanation, the researcher can be confident that such difference is caused by the intervention.

An independent variable affects another variable. A dependent variable is affected by another variable.

Ordered from low to high, the levels of measurement are nominal, ordinal, interval, and ratio. At the nominal level, one may classify a variable’s values into separate categories but these categories may not be ordered.

At the ordinal level, one may classify and order values but one may not determine differences between values. In a rank ordering, objects are ordered on some characteristic from highest to lowest. The object’s position in that ordering is their rank. Rank orderings are at the ordinal level.

Variables measured at the interval level have numeric values, and hence, using subtraction, differences between values can be determined. Because the zero point of the measurement scale is not a true zero, one that conveys the absence of the quantity being measured, ratios are not meaningful for interval-level variables. When the zero (0) on the measurement scale is a true zero, ratios are meaningful, and hence, measurement is at the ratio level.

Different statistical procedures are used with variables at different levels of measurement. An exception is that the same statistical procedures are almost always used for interval- and ratio-level variables. This being so, these levels are grouped into a single level, the interval/ratio level. Almost always, one should measure at the highest possible level of measurement.

A multi-item scale consists of multiple items, each of which probes some aspect of a concept. Adapting a pragmatic stance, this text treats scores on multi-item scales as being at the interval/ratio level of measurement.

1.11 PROBLEMS AND QUESTIONS

Section 1.2

1. Social work practice based on the “best scientific evidence available” (Rubin, 2010, p. 315) is termed __________-_________ practice.

Section 1.3

2. The theoretical side of science is termed __________, and the applied/observational side is termed __________.

3. The observations that one gathers are termed __________.
4. The two basic social science research methods are _________ methods and _________ methods.

5. _________ research methods emphasize objective measurement. _________ research methods emphasize depth of understanding and deeper meaning.

6. Indicate whether each of the following demonstrates quantitative or qualitative research methods.
   a. Questions on a questionnaire ask respondents to choose between the responses “yes,” “no,” or “not sure.”
   b. A researcher conducts in depth, deeply probing interviews asking children placed in foster care to share their personal feelings about the foster care experiences.
   c. A scientist records how long it takes rats to run a maze in two different situations.
   d. A researcher interviews in depth seven children who were adopted when older and produces “vignettes” of the unique experience of each one.
   e. A researcher rides motorcycles for a year with members of a motorcycle club. She gains first-hand, personalized experience of the “culture” of the club and develops an article on this.
   f. Youth who have been delinquent take part in a program designed to reduce delinquency. A researcher examines arrest records for these youth and develops a report based on these records.
   g. Some students in a statistics class receive tutoring from a teaching assistant. Others complete a computer-based statistics module. The professor compares grades on the final exam for the two groups and develops a report.

7. Indicate whether each of the following is applied research or pure research.
   a. A researcher examines whether a change in the nutritional content of school lunches leads to better health in an elementary school.
   b. A scientist studies the structure of the atom for the pure joy of learning.
   c. A social worker examines whether a behavior management program leads to better behavior among school children.

Section 1.4

8. Each individual unit on which measurements are recorded is a _________.

9. A variable is something that takes on different _________.

10. What are the values of the variable sex?

11. _________ take on only one value.

12. Is 3.1416 (π) a variable or a constant?

13. _________ variables are numeric. _________ variables are nonnumeric.
14. Is the variable height (as it is most often measured) a quantitative or a qualitative variable?

15. Is the variable sex qualitative or quantitative?

16. A term synonymous with qualitative variable is _______ variable.

17. Indicate whether each of the following variables (as they are most commonly measured) is a quantitative (numeric) or a qualitative (categorical) variable.
   a. Number of movies seen in the last month.
   b. Whether (yes or no) you enjoy football games.
   c. Your score (percentage correct) on your last test.
   d. Favorite kind of music: rock, jazz, classical, hip-hop, and so on.
   e. Eye color (blue, brown, green etc.).

18. A _______ variable has exactly two categories. Another name for a dichotomous variable is a _______ variable.

Section 1.5

19. _______ samples, also known as _______, are selected by methods of chance.

20. This text refers to those selected to be in a research study as the _______ ________.

21. Indicate whether each of the following is a random sample or a nonrandom sample.
   a. A computer program generates a random list of clients who will participate in a follow-up study.
   b. Social workers, working from memory, provide a list of clients who they believe would want to participate in a follow-up study.
   c. Clients who keep their appointments participate in a study. (Those who do not participate.)
   d. One hundred students are selected by “the luck of the draw” to take part in a campus opinion survey.
   e. An interviewer at a shopping mall stops shoppers, asking them if they want to complete a questionnaire.

Section 1.6

22. A statistic is a _______ ________ of data (Toothaker & Miller, 1996).

23. Indicate whether the researcher is engaging in descriptive statistics or inferential statistics.
   a. A student organization studies responses of a random sample of university students for the purpose of drawing conclusions about the population of students at the university.
   b. A professor administers a questionnaire to students in her class and writes an article about these opinions.
c. A researcher obtains data about the residents in a nursing home and writes about their situations.
d. The National Association of Social Workers (NASW) selects a random sample of its members and mails them a survey. It studies the sample’s responses to learn about the full NASW membership.

24. Indicate whether each of the following demonstrates a correct or incorrect use of inferential statistics. Consider the use as correct only if the researcher uses a random sample to draw conclusions about the particular population from which the sample was selected.
   a. A professor determines the opinions of social work students who are taking her class in social welfare policy and, based on this sample, draws conclusions about all social work students at her university.
   b. Community residents who attend a community meeting about violence in their community fill out a questionnaire on violence. The meeting’s organizers tabulate responses and, based on them, draw conclusions about all members of the community.
   c. A random sample of students from University X responds to a poll on political attitudes. A professor uses these responses to write a report about the political attitudes of all students at University X.
   d. A random sample of students from University X responds to a poll on political attitudes. A professor uses these responses to write a report about the political attitudes of all students at University Y.
   e. A mental health clinic administers a survey on client satisfaction to a random sample of its clients. It uses this survey to draw conclusions about all of its clients.

25. Indicate which variable in each pair is the independent variable and which is the dependent variable. Or it may be that the variables cannot be classified as independent or dependent, in which case respond “cannot be classified.”
   a. A researcher studies the effect of therapy (one variable) on assertiveness (other variable).
   b. A researcher monitors the relationship between amount of exercise (one variable) and blood pressure (other variable).
   c. A professor examines the association between number of hours studying for an exam (one variable) and grade on the exam (other variable).
   d. A researcher finds an association between self-esteem (one variable) and happiness (other variable). (Hint: Difficult one to answer.)
   e. A “token economy” (one variable) is developed to help an elementary school student reduce disruptive classroom behavior (other variable).

Section 1.7

26. Indicate whether the application demonstrates univariate, bivariate, or multivariate statistics.
   a. A researcher examines the relationship between visiting of nursing home residents and the level of happiness of these residents.
   b. A poll reports that 57% of respondents support Legislation X.
c. A researcher examines whether handedness (right vs. left) is associated with the choice of major (natural sciences vs. social sciences vs. humanities).
d. A researcher finds a relationship between levels of exercise and blood pressure but wonders whether this relationship may be caused by a confounding variable, and therefore examines this possibility.
e. In a single equation, a researcher examines the effects of several variables—income level growing up, family structure (one parent vs. two parent family), education level—on income earned at age 30.
f. A professor finds that the average number of movies seen by students in her class in the last month is 3.7.

27. Respond true or false.
   a. Whenever one finds that two variables are associated in a random sample, one knows assuredly that these variables are associated in the population from which the sample was selected.
   b. At the risk of oversimplifying, with a random sample, only the “luck of the draw” causes differences between the characteristics and opinions of those in the sample and the characteristics and opinions of those in the population from which the sample was drawn.

28. ________ ________ ________ examine whether study sample results are likely to be caused by the luck of the draw.

29. The third variables that bring about relationships between other variables are often termed ________ variables.

30. See if you can think of a confounding variable or variables that might provide an alternative to the conclusion the “researcher” reaches about the cause of each relationship. There is no right or wrong answer to these.
   a. Some students volunteer to take part in a health fitness program. Others do not volunteer for this program. After the program has ended, those who took part (the volunteers) have, on average, lower blood pressure than those who did not take part. A researcher concludes that the fitness program caused the low blood pressure.
   b. A student researcher finds that students who volunteer in community projects score higher on a “happiness” scale than do students who do not volunteer. The researcher concludes that participation increases happiness.
   c. A child welfare researcher finds that children adopted by their foster parents are less likely to require mental health services than are children adopted by “new” adoptive parents. The researcher concludes that adoption with new adoptive parents (rather than with prior foster parents) causes mental health problems.

Section 1.8

31. ________ refers to the methods used to assign participants to groups.

32. ________ ________ is the use of methods of chance to assign participants to ________.
33. Indicate whether each of the following studies uses random assignment.
   a. One group consists of persons who volunteer to participate in a stop smoking program. A second group consists of persons who smoke about the same number of cigarettes but who do not volunteer.
   b. A researcher studies children in foster family homes (one group) and children in group homes (the other group), looking to see which group has better outcomes.
   c. Some elderly persons have pets (one group). Others do not (the other group). A researcher examines happiness in these groups.
   d. Fifty nursing home residents are selected to participate in a study. One half are randomly selected to receive visitation by a therapy pet and one half are randomly selected not to receive such visitation. Depression levels are studied.
   e. A professor selects randomly from a hat some students to receive tutoring on a computer and (again randomly) some students to receive tutoring from a teaching assistant. Scores on the final exam are compared.

34. Respond true or false.
   a. In studies that use random assignment, the researcher should be quite concerned that a confounding variable or variables is affecting study results.
   b. In studies that do not use random assignment, it can be extremely difficult if not impossible to determine whether a study result is caused by the intervention or by a confounding variable.
   c. Generally speaking, random assignment to groups increases the researcher’s confidence that the study results are caused by the intervention rather than by a confounding variable.

Section 1.9

35. When variables are at the nominal level, one may _________ responses into categories. At the ordinal level, one may also _________ responses/categories. At the interval level, one may speak meaningfully about the _________ between values. At the ratio level, _________ become meaningful.

36. All rank orderings are at the _________ level of measurement.

37. At the ratio level of measurement, “0” may be regarded as a _________ zero rather than an arbitrary one. Zero on a ratio-level scale conveys the _________ of the quantity being measured.

38. In your own words, why does not it make sense to say that 10 °F is twice as hot as 5 °F?

39. Indicate the level of measurement for each of the following:
   a. Shoe size as measured in the United States
   b. Social class (lower, middle, upper)
   c. Weight measured with a scale
d. Political party (Republican, Democratic, etc.)
e. Students rank order themselves according to the amount of time that they spent studying
f. Religion (Christian, Hindu, Buddhist, Native American Church, other)

40. This text recommends treating the numbers that are sometimes assigned to the values of categorical variables as __________ rather than numeric quantities.

41. As a general rule of thumb, one should measure at the __________ possible level of measurement.

42. Respond true or false.
   a. Many statistical procedures are appropriate only for variables at particular levels of measurement.
   b. Whether a variable is considered to be at the interval level versus the ratio level often has important consequences for the basic introductory statistical procedures that may be used.
   c. The individual items that are summed together to develop scores on multi-item scales are at the interval/ratio level of measurement.
   d. In a formal and mathematical sense, scores on multi-item scales are (without question) regarded as being at the interval/ratio level of measurement.
   e. Pragmatically, most researchers view scores on multi-item scales as being at or very nearly at the interval/ratio level of measurement.
   f. So far, statistics is fun.