I

Course Preparation

Chapter 1

Teaching Statistics

A beginning

> *For some students, it is the course about which their peers have warned them. They have heard the horror stories and believed them. (Schutz, Drogosz, White, & DiStefano, 1998, p. 292)*

Statistics as both a course to take and one to teach has a dreaded reputation. If they are able, students invariably put off the course to the very last moment and appear visibly anxious on the first day of class. They seem to believe the scuttlebutt that any statistics course really deserves the title, "Stadistics." Of course, faculty are not much better. Our departmental chairperson joked that he does not like the three of us who teach statistics traveling together to a conference. "What if something happened! Who would teach statistics?" If truth be told, most of our colleagues, with a bit of time to prepare, could teach introductory statistics. However, they also seem to believe the mythology that the course is a drudge and more importantly, the notion that the course is ripe for less than stellar course evaluations.

However, nothing could be farther from the truth. Statistics can be one of the most fun and gratifying courses to teach. When we talk to fellow statistics teachers at various conferences, it is not unusual for one of us to comment on how much we enjoy teaching statistics. Oddly, what we have noticed is that individuals will often lower their voices a tad and look around before expressing similar thoughts.

It is as if some teachers do not want others to know about one of the best-kept secrets in academia. Teaching statistics can be eminently rewarding and, more importantly, meets a fundamental need in helping students develop a solid knowledge foundation in psychology.

Nonetheless, as Mulhern and Wylie (2004) commented, "Teaching statistics and research methods to psychology undergraduates is a major pedagogic challenge" (p. 355). The challenge, however, lies not with the complexity of the material, which ranges in difficulty from easy to conceptually complex, but rather with the type of information communicated. Evans (1976) provided an interesting perspective on the differences between teaching most content-oriented courses in psychology and quantitative methods courses. In most content courses, we teach students to "know that," whereas in statistics we teach students to "know how." Evans draws the following apropos analogy: Teaching statistics via lecture and handouts, with a clear explication of concepts, is as useful as providing someone with a lecture and handout on how to ride a bicycle. The pedagogical challenge for statistics teachers is to move beyond the lectern, put away the static PowerPoint (the current equivalent of yellowing notes), and to try out some alternate teaching strategies.

Students also face new challenges when taking statistics or research methods courses for the first time. Unfortunately, students may perceive these challenges principally as threats versus opportunities. This point is particularly true for those students who may not utilize sophisticated learning techniques. If students have succeeded primarily by studying in spurts, memorizing materials, or relying heavily on recall for exams, they may find statistics to be difficult terrain to navigate. Hence, the familiar lament from struggling students that they feel "lost" in the course. If students cling to their traditional study methods and learning strategies, they may experience a drop in their usual performance level and hence, a subsequent drop in their self-efficacy in relation to the course, which can then spiral into a well of deepening frustration and potential failure. Therefore, statistics teachers might consider structuring their courses in ways that facilitate new and more adaptive learning strategies.

The aim of this book is to provide statistics teachers with the best information available to assist in the development or restructuring of their statistics course. We designed this book to meet the needs of both novice and seasoned teachers of statistics. In addition, we have created a companion Web site (www.teachstats.org) that contains additional instructional techniques, activities, topics, and resources.

Throughout it, we provide information concerning a range of topics from pedagogical methods and activities designed for teaching specific concepts to broader issues related to the unique learning needs of statistics students. We draw heavily on the small but growing empirical and scholarly literature related to the teaching of statistics in each chapter (Becker, 1996). As a result, this book extends beyond the content you might typically find in an instructor's manual. Our goal is to introduce you to the best practices in teaching statistics so that you can turn a potential course prison—the incoming perception of many students—into a pedagogical haven for learning.

So Why Teach Statistics?

Although statistics may be tangential to your primary area of research, it is beneficial to examine why the course is an important one to teach. After all, if you do not find meaning in the material, neither will your students. On the most transparent level, it simply is a good idea for everyone to have a basic understanding of statistics. In other words, knowledge of elementary statistics is an end goal in itself. In today's world, statistical literacy is fundamental given the tendency for the media, politicians, and corporate America to deluge us daily with quantitative information (Ben-Zvi & Garfield, 2004; Gal, 2004; Rumsey, 2002; Utts, 2003). Individuals need to be able to make sense of numerical information to avoid falling prey to the influence of data that looks incontrovertible simply because it is quantitative in nature. Over a half century ago, Wishart (1939), an early statistician, commented that the teaching of statistics is important because it protects individuals from the misleading practices of "the propagandists" (p. 549). It is just as important an issue today.

Two similes often describe the teaching of statistics. Hotelling (1940), perhaps best known for the multivariate technique called Hotelling's T, remarked that teaching students statistics is like teaching them to use a tool. More commonly, instructors comment that teaching of statistics is like teaching a foreign language (Hastings, 1982; Lalonde & Gardner, 1993; Walker, 1936). Both comparisons are insufficient, as they emphasize discrete skills that, once learned, students may fail to apply to other domains of knowledge or to the broader research process. Hence, one can learn to use a power sander and circular saw but not necessarily see any connection from those skills to building a doghouse. Students need to be able to apply their underlying knowledge to other contexts. We also do not want students to perceive statistics as a foreign language requirement only to be left unvisited once completed. It is imperative that students come to see statistics as a set of critical thinking skills and knowledge structures designed to enhance their ability to explore, understand, reason, and evaluate psychological science. In teaching the course, instructors need to make connections to material from other courses to emphasize the role that research methods and statistics plays in creating a foundation for the study of psychology as well as other disciplines.

We all cringe when we see a paper handed in that has as its most scholarly reference, *Rolling Stone* or *Newsweek*. Students need to be able to read and evaluate the empirical literature. This ability is particularly important given the dangers associated with blindly trusting the translations presented in the popular press. Consequently, we often ask our students how many of them actually read the results section of an empirical paper and how many simply skip over that section hoping that the author will eventually put it into English for them. Sheepishly, a large percentage of our students confess to such practices. As demonstrated by Rossi (1987), the statistical computations themselves in journal articles may even be incorrect. Therefore, our students need basic statistical literacy, thinking, and reasoning skills with which to begin their evaluation of empirical results. Buche and Glover (1980) demonstrated that students who are provided with training in the fundamental skills necessary to review and study research articles, particularly in relation to methods and an understanding of statistical techniques, are better able to read, evaluate, and appreciate research in their field. Thus, such training is not only essential in their other coursework, but also beneficial for their future careers regardless of whether they choose a path as a researcher, clinician, lawyer, manager, or medical practitioner.

Hotelling (1940) commented that "a good deal of [statistics] has been conducted by persons engaged in research, not of a kind contributing to statistical theory, but consisting of the application of statistical methods and theory to something else" (p. 465). The vast majority of our students will not develop careers specializing in quantitative methods or theory. However, we may hope, and in some instances require, that our students engage in research as part of a class project or independent study. Unfortunately, not all students immediately see the connection between research methods and statistics. They may hold the false belief that one can simply design a study, collect data, and then hire a statistician to analyze those data. Of course, the concepts of research methods and statistics are inextricably interwoven and students must recognize the interrelationships to conduct research effectively. Indeed, students must begin their statistical planning while designing their study.

Finally, and perhaps it should go without saying, psychology is a science. Thus, research methods and statistics are foundation courses necessary for understanding and critically evaluating all of the research presented, studied, and evaluated in the remainder of our students' coursework. Psychology instructors can enhance students' appreciation of statistics by drawing connections to other content-focused domains of psychology. Although taking statistics alone does not decrease students' beliefs in pseudoscientific claims (Mill, Gray, & Mandel, 1994), statistical literacy combined with other content-focused coursework stressing research evaluation, may better prepare our students to be critical consumers of information both within and outside of psychology.

Historical Pedagogical Controversies

Occasionally, one may hear statistics teachers state that they love teaching the course because the material never changes. This point is simply not true. Although there is much that has remained the same, the field of statistics and its application to psychological research is constantly developing. Three main pedagogical controversies have been associated with the teaching of statistics since the field was in its infancy: (a) who should teach statistics; (b) the use of statistics labs and technology; and (c) the content of statistics courses.

Who should teach statistics?

One source of discussion among statisticians, decades ago, was the question of who should teach statistics. Should statisticians and mathematicians be the only individuals allowed to teach statistics or is it more appropriately taught within the departments, such as psychology, conducting research? Wishart (1939) argued that non-statisticians should not teach statistics. He believed that such practices were fraught with danger, as non-statisticians were unprepared to handle the difficulties of teaching and supervising statistical research. However, Fisher (1937) felt that the goal of teaching statistics should be toward the application of these concepts to research in one's field and he argued for offering statistics coursework in research departments such as psychology or biology. Hotelling (1940) commented that professors usually do not want to teach a class outside their main area of interest. He noted further that anyone attempting to digest mathematical statistics outside of one's discipline faces a largely unreadable task. Therefore, he made a case for individuals within particular disciplines keeping current with the quantitative methods literature in their field and teaching the statistics course within respective academic departments. Although some individuals may feel unprepared to teach statistics due to a lack of extensive training in quantitative methods, Hotelling argued that being an excellent mathematician is, in and of itself, a poor predictor for becoming a good statistics instructor. Rather, Hotelling stated that in addition to knowledge of the fundamentals, statistics instructors need to have "a really intimate acquaintance with the problems of one or more empirical subjects in which statistical methods are taught" (p. 463). Accordingly, psychologists today are in a good position to make the world of statistics contextually meaningful for students by relating statistical concepts to applied problems in psychology.

By 1950, it was evident that psychology had adopted Hotelling's (1940) approach to teaching statistics and the majority of psychology departments included coursework in statistics, research methods, experimental, and tests and measurements (Sanford & Fleishman, 1950). More recently, approximately 77% of universities and colleges required statistics courses within departments of psychology (Bartz, 1981). According to Garfield (2000), today's students receive the vast majority of statistical training from instructors outside the field of mathematics (e.g., education, psychology). Many individuals who teach statistics within psychology departments do not have quantitative methods as their primary focus of scholarship (Hayden, 2000). The departmental location of a statistics class may reflect philosophical differences and pragmatic concerns due to limited numbers of faculty within any one department (Fraser, 1962; Friedrich, Buday, & Kerr, 2000; Perlman & McCann, 1999).

Statistics labs and related technology

Many early statisticians cared deeply about the pedagogy of statistics and endeavored to sort out best practices in relation to their craft. For example, there was uniform agreement that teaching statistics primarily through lecture was a death knoll for learning. Indeed, Cohen and Firestone (1939) commented that "a lecture is a process whereby the notes of the professor become the notes of the student without passing through the minds of either" (p. 714). Although there was agreement on some issues related to teaching methods, there were still significant areas of disagreement among statistics instructors. For example, Walker (1936) and Olds (1954) argued for the importance of laboratory work. On the other hand, Cohen and Firestone stated that a lecture–laboratory combination was not enough to facilitate learning and only assisted the best students. They suggested that students take smaller, informal statistical workshops designed to provide them with the opportunity to learn a range of concepts and apply these techniques to real-world problems.

Few teachers today would argue that lecture alone is ideal for any course. However, Perlman and McCann (1999) found that only 12% of statistics courses included an identified laboratory component. Although one can argue that Perlman and McCann's methods may have undercounted the number of available statistics courses including a laboratory experience, the reported limited availability of laboratory experiences for students studying statistics is still a potential concern.

The Guidelines for Assessment and Instruction in Statistics Education (GAISE) Project (American Statistical Association: ASA, 2005) noted that the biggest change in the teaching of statistics over the past decade was the increased use of technology. Interestingly, the use of technology as a means to assist faculty and students with the computation of data was also an issue for the early statisticians. For example, Wishart (1939) argued that teachers should only introduce students to "calculating machines" after they had enough practice computing data by hand (p. 547). He also stressed that everyone in the class should have access to their own machine. Clearly, the argument for a well-stocked lab predates the use of computers. Although we occasionally witness the media lament that students just are not as mathematically literate as they were years ago, early statisticians also remarked that not all of their students appeared to be mathematically prepared. Walker (1936) expressed concern that some students appeared to spend hours working formulas and checking for errors at the expense of genuinely understanding the concepts behind formulas. She further mused that some students appeared to spend an inordinate amount of time fruitlessly attempting to read the textbook.

Content of statistics courses

There is relatively little debate as to the importance of including statistics as a core area in psychology. The St. Mary's Conference included statistics and methodology as a core content area within psychology (Brewer, 1997). Understanding research methods, including knowledge of data analytic techniques, is one of the learning goals listed in the *APA Guidelines for the Undergraduate Psychology Major* (American Psychological Association: APA, 2006). Basic statistical concepts from descriptive through inferential are also included in the *National Standards for High School Psychology Curricula* (APA, 2005).

Psychology departments have largely complied with the recommendations put forth by the APA regarding the infusion of statistics into the curriculum. For example, Bartz (1981) found that the majority of psychology programs required coursework in statistics either through their own department or through another department on campus. More recently, Friedrich et al. (2000) sampled top ranking national and regional universities/colleges (defined according to *U.S. News & World Report*) as well as an unranked sample of colleges on a range of variables related to the teaching of statistics. Based on the 255 returned surveys, Friedrich et al. found that the 93% of departments included one or more courses devoted entirely to statistics. Moreover, Perlman and McCann (1999) found in a survey of 500 college catalogs that introductory psychology, a capstone course, and statistics composed the core course requirements at the majority of institutions they surveyed.

Although departments have been quick to adopt statistics as a core course in their curriculum, they have been reticent to adopt many of the concepts recommended by the APA Task Force on Statistical Inference (Wilkinson & the Task Force on Statistical Inference, 1999). For example, this task force argued for greater inclusion, both in data analysis and reporting, of effect sizes, confidence interval estimation, and statistical power. Unfortunately, Friedrich et al. (2000) found most teachers included one hour or less on these topics. Instead, they found that most introductory statistics courses covered traditional topics such as correlation, independent t-tests, and one-way ANOVA. Byrne (1996) argued that psychology was lagging behind other disciplines in clinging to teaching traditional quantitative methods. She stated that instructors ignored topics such as path analysis, multivariate techniques, time series analysis, and analysis of covariance methods in introductory statistic courses. She further commented that the course excluded field research in favor of basic laboratory methods and statistical analysis.

One might argue that these newer themes are unnecessary in an introductory statistics course. However, as Friedrich et al. (2000) highlighted, the introductory course serves as a "conceptual framework" for future courses given students are encouraged to think about statistics within a research context. Giesbrecht, Sell, Scialfa, Sandals, and Ehlers (1997) noted that many students would only take one statistics course in their entire academic career. If instructors do not introduce these concepts to students in the first course, they may never see them during their undergraduate training. Byrne (1996) argued that several problems arise from not teaching current techniques in the course. First, students and future researchers may design studies that are less than optimal to address the research question being asked, potentially leading to false conclusions. Second, the information presented in journals may fail to include much needed analyses such as effect sizes and instead demonstrate an "over-reliance on evidence of statistical significance, with little or no attention paid to practical significance" (p. 78). Finally, students may be unprepared for future positions in psychology, higher education, business, or other fields due to lack of familiarity with the newer techniques expected by future employers.

Statistics in Relation to the Discipline

Many students put off taking a course in statistics until the very end of their undergraduate studies because they fear the difficulty of the course (Barnette, 1978). Of course, this educational strategy makes little sense on either a pragmatic or a logical level. Therefore, most departments recommend that students take statistics and research methodology coursework early in their academic careers, given that these courses provide the necessary foundation upon which to take more advanced coursework in psychology (Friedrich et al., 2000; Lauer, Rajecki, & Minke, 2006).

Although psychology departments as a whole seem to prefer that students undertake quantitative methods courses early, students seem to be of a different opinion. Lauer et al. (2006) examined the transcripts of psychology major alumni from four different universities. For all universities, a significant difference was found between when students completed non-methodological psychology courses (e.g., abnormal or cognitive) and methodological coursework. Students consistently completed quantitative methods courses later in the academic careers. This finding is not surprising, given researchers have revealed that psychology majors tend to prefer "human interest" courses such as developmental or personality as opposed to methodological courses (Rajecki, Appleby, Williams, Johnson, & Jeschke, 2005).

Lauer et al. (2006) suggested that departments consider the following recommendations to counter student bias against quantitative methods courses and to ensure that such courses are taken early in a student's academic career. First, offer a lower-level methods course with no prerequisites. Second, require students to take more than one methods-related course. Third, develop a hierarchically structured curriculum organized such that the quantitative methods course is a requirement for future coursework. Finally, and perhaps most importantly, articulate the link between developing statistical, research, and technical skills and future success in more applied psychology courses and in the job market.

Currently, there appears to be little consistency across departments in relation to statistics serving as a prerequisite for other courses. In their survey of psychology departments, Friedrich et al. (2000) found that only 15% of departments required introductory statistics as a prerequisite for "most" of their intermediate or advanced courses. In fact, many of the respondents revealed that statistics either was not required (22%) or was a prerequisite for "only a very few" intermediate or upper division courses (45%).

Although making statistics a prerequisite for additional content courses might be pedagogically sound, doing so has at least one important pragmatic implication. Individuals who are fearful of statistics might avoid psychology classes altogether if a statistics course was a prerequisite. Thus, potential majors might be lost. Additionally, students from other disciplines might also not register for more advanced psychology coursework if statistics was a prerequisite. Consequently, prerequisites might have the unintended consequence of reducing class registrations—an issue at many institutions, particularly smaller schools.

Sequence of the Class and Topics

Teachers must decide what material is optional or imperative to teach and in what order. Most individuals who teach statistics find themselves faced with too much information to teach in too short a time. They must strive to balance the needs of heterogeneous students of variable abilities. You do not want to sacrifice rigor leaving the best students in a state of perpetual boredom, but you also do not want to present the information in such depth that you leave other students behind. This challenge is not a new one. Walker (1936) compared the teaching of statistics to "walking a tightrope" (p. 610). In terms of sequencing, teachers face a challenge to integrate fundamental statistical concepts and ideas. As we tell our students, learning certain concepts will be like constructing a picture puzzle. The entire picture may not be clear until we have put all of the pieces in place.

An introduction to statistics covering a range of essential topics is often useful to students later as they take coursework in other departments or pursue career opportunities that require a broader range of quantitative knowledge (Giesbrecht et al., 1997). For those students seeking a more in-depth study of methods and statistics, departments can always offer advanced coursework. Walker (1936) suggested that departments offer three different introductory statistics courses: (a) statistics for students who plan to become statisticians; (b) statistics for students who plan on research careers; and (c) a statistical appreciation course for students who want to develop a general statistical literacy. However, then as now, most universities do not have the staffing required to offer such a range of introductory courses.

Bossley, O'Neill, Parsons, and Lockwood (1980) recommended that teachers begin the course with a general overview of both descriptive and inferential statistics, thereby providing a conceptual framework for use throughout the course. Such a cognitive map would enable students to conceptualize the overall schema of the course and the material to be covered. They also noted that teachers might introduce nonparametric statistics early in the semester, as this material tends to be less challenging mathematically. Therefore, teachers can place a greater emphasis on introducing ideas such as significance levels and statistical power as opposed to teaching complex mathematical formulae. Finally, they suggested that an introductory statistics course should focus on a broader understanding of the material to build general statistical literacy as opposed to developing specific skills.

Two studies have identified the most important topics to teach in the introductory statistics course. Giesbrecht et al. (1997) compiled a list of statistical topics based on an evaluation of research articles and statistics textbooks. Forty-four professors who taught at least one statistics course at the introductory level ranked the importance of each topic. The results revealed 49 topics that fell into the following nine categories: (a) summarizing data and graphs (e.g., frequency histograms, regression lines); (b) summarizing data using descriptive data (e.g., measures of central tendency and variability); (c) probability and probability distributions (e.g., normal distribution, central limit theorem); (d) estimation (e.g., sampling distributions, least squares estimation); (e) hypothesis testing (e.g., t-tests, Type I and Type II errors); (f) categorical data analysis (e.g., chi-squared test for independence); (g) correlation and regression; (h) ANOVA; and (i) nonparametric tests. Readers may also be interested in a similar analysis conducted on core topics in teaching research methods (see Giesbrecht et al., 1997).

Because Giesbrecht et al. (1997) used professors representing four different disciplines, it is possible that their results do not accurately reflect of the perspectives of psychologists who teach statistics. Landrum (2005) conducted a study to identify the primary topics of importance in an introductory statistics course for psychology students. Using a similar procedure, he compiled a list of statistical terms appearing in statistics text and used a mail survey to psychology departments. Faculty who taught statistics and participated in the survey rated the importance of each concept on a four-point scale ranging from "not at all important" to "extremely important." Based on the return of 190 surveys, Landrum developed his Top 100 list (see Table 1.1). This study, together with Giesbrecht et al.'s findings, provides teachers with the most important concepts to cover in an introductory statistics course.

Finally, instructors rarely address tests and measurement within the introductory statistics course. This point most likely reflects pragmatic concerns such as time limitations and staffing issues. Nonetheless, to augment the introductory course, Friedrich et al. (2000) recommended the addition of an advanced hybrid course that combines research, statistics, and measurement into the curriculum.

Regardless of topics covered or course sequencing, the GAISE Project (ASA, 2005) recommended six strategies for teaching statistics:

1. Emphasize statistical literacy and develop statistical thinking.
2. Use real data.
3. Stress conceptual understanding rather than mere knowledge of procedures.

Table 1.1 Landrum's (2005) Top 100 List

1. Normal curve
2. Statistically significant
3. Bell-shaped curve
4. Significance level
5. Hypothesis testing
6. Normal distribution
7. Standard deviation
8. Sample
9. Alpha level
10. Mean
11. Null hypothesis
12. Central tendency
13. Inferential statistics
14. Variability
15. Arithmetic mean
16. Correlation
17. Pearson correlation
18. Dependent variable
19. Two-tailed probability
20. Positive correlation
21. Data
22. Hypothesis
23. *t* test
24. Descriptive statistics
25. Variance
26. Negative correlation
27. Not significant
28. Variable
29. Population
30. Statistic
31. Level of significance
32. Critical values
33. Type I error
34. Degrees of freedom
35. Median
36. Significant effect
37. Rejection region
38. *t*-test for independent-samples design
39. One-way ANOVA
40. Statistical inference
41. Two-tailed test of significance
42. *t*-test for independent groups
43. *t*-statistic
44. Standard error of the mean
45. Critical region
46. Standard error
47. ANOVA
48. Inferential process
49. Alternative hypothesis
50. *F* ratio
51. Deviation
52. Distribution of sample means
53. Student's *t* test
54. Linear relationship
55. Independent-samples design
56. *z* score transformation
57. Random
58. Random assignment
59. Sampling error
60. Correlational method
61. *z* score
62. Null-hypothesis population
63. Frequency
64. Independent groups design
65. Frequency distribution
66. Independent variable
67. Type II error
68. One-tailed probability
69. Random selection
70. Nondirectional hypothesis
71. Sampling distribution
72. Estimated population standard deviation
73. Overall mean
74. Correct decision
75. Sampling distribution of the mean
76. Sampling distributions of a statistic
77. Regression
78. Causation
79. Scatterplot
80. Sum of squares
81. Positive relationship
82. Sampling distribution of *t*
83. Sum of squared deviations
84. Test statistic
85. Chi-square distribution
86. Between-groups sum of squares
87. Simple random sample
88. Population variance
89. Random sampling
90. *t*-distribution
91. Chi-square statistic
92. One-tailed test of significance
93. Probability
94. Standard score
95. *F* distribution
96. Distribution of scores
97. ANOVA summary table
98. Treatment
99. Levels/treatments
100. Subjects/participants

4. Foster active learning in the classroom.
5. Use technology for developing conceptual understanding and analyzing data.
6. Use assessments to improve and evaluate student learning. (p. 1)

Throughout this text, we will discuss research supporting the above recommendations and describe the best teaching practices to translate these recommendations into statistics learning outcomes.

Introducing Research Methods within the Context of Statistics

The story of research methods and statistics is the story of the chicken and the egg. Can one conduct research without some knowledge of statistics and can one truly understand the fundamentals of statistics without some knowledge of research methods? Certainly, in departments of psychology around the country, prerequisites for both statistics and methods courses vary. In addition, many departments have opted for a combined research methods and statistics course or a sequence of integrated courses (Friedrich et al., 2000).

Byrne (1996) argued that students do not develop an appreciation, let alone an excitement, about studying statistics until they see real-world applications of statistical concepts and methods. She argued that all statistics courses should include an applied research component. In other words, students should be able to work with and make practical sense of data sets provided for the course.

The value of student involvement in research includes not only the development of a greater appreciation for statistics but extends to an increased understanding of them as well (Pfannkuch & Wild, 2004; Starke, 1985). One key component of statistical literacy is the ability to apply statistical thinking correctly to different situations. In their own lives, in evaluating media information, or in reading research, students do not regularly arrive at accurate conclusions when the situation involves issues of statistics or probability (Schwartz & Goldman, 1996). Instead, students tend to rely on "statistical heuristics to reason and make judgments about the world" (Nisbett, Krantz, & Jepson, 1983, p. 339). Unfortunately, these statistical cognitive shortcuts are not always useful and may lead to faulty conclusions. Friedrich et al. (2000) concluded that greater learning in statistics courses results when methods used to teach statistics highlight reasoning, understanding, and interpretation of data rather than merely the computation of statistical formulas. As research opportunities facilitate both critical and independent thinking (Starke, 1985), instructors can accomplish the goals outlined by Friedrich et al. by incorporating research methods into their statistics courses. Conversely, statistics education increases reasoning skills across a variety of domains and thus, may facilitate the study of research methods (Kosonen & Winne, 1995).

In addition, Thompson (1994) recommended that teachers include research as a fundamental component of any statistics course. However, he stressed that students generate their own data for analysis as opposed to being passive recipients of pre-existing data sets. He also emphasized that involvement in the collection of data and the development of specific research questions for testing generates greater excitement for learning statistics (see also ASA, 2005; Bradstreet, 1996; Cobb & McClain, 2004; Jewett & Davies, 1960; Rumsey, 2002; Singer & Willett, 1990; Stallings, 1993; Tanner, 1985; Thompson, 1994). We will discuss this topic more in subsequent chapters.

Student Populations

The far-ranging heterogeneity of undergraduate statistics students provides a wonderful backdrop for discussion, exploration, and learning of new course content. However, such diversity also creates challenges. The most commonly noted concerns for teachers include variability in mathematical ability, cognitive abilities and learning styles, and attitudes and motivation toward learning statistics (Schutz et al., 1998; Tremblay, Gardner, & Heipel, 2000).

Mathematical ability

Quantitative literacy and statistical literacy are distinct but interrelated concepts (delMas, 2004; Moore, 1998). Research examining the development of students' statistical knowledge base in middle and high school demonstrates that general math courses often ignore concepts related to statistics and probability (Wilkins & Ma, 2002). Using data drawn from the national *Longitudinal Study of American Youth* study (LSAY: Miller, Kimmel, Hoffer, & Nelson, 2000), Wilkins and Ma documented the progressive rate of student learning related to algebra, geometry, and statistics during middle and high school. The LSAY followed a cohort of 3,116 middle to high school students over a period of 6 years from 12 different geographic areas. Each year, students completed measures of mathematics achievement, mathematics attitude and self-concept scales, and other background information. Using hierarchical linear modeling, Wilkins and Ma measured patterns of growth for each student related to mathematical learning. They found that learning rates related to statistics literacy lag far behind the other two content areas. For example, the growth rate of algebra learning is three times that of statistics at the high school level. Wilkins and Ma (2002) hypothesized that, at the secondary school level, concepts related to statistics and probability topics are often in the "back of the book" (p. 296) and thus rarely covered.

As a result, many undergraduate students arrive on college campuses unprepared to study advanced mathematics or statistics (Brown, Askew, Baker, Denvir, & Millett, 1998; Mulhern & Wylie, 2004; Phoenix, 1999; Tariq, 2002). Additionally, high school seniors in the United States lag behind students in other countries on measures of mathematical literacy (Mullis, Martin, Beaton, Gonzalez, Kelly, & Smith, 1998). The lack of mathematical ability among many incoming students may haunt them in future statistics courses given the reported positive correlations between highest mathematical grade level completed, mathematical achievement, and performance in an introductory statistics course (Lalonde & Gardner, 1993).

Unfortunately, the situation may be worsening. Mulhern and Wylie (2004) argued that mathematical competencies are uniformly decreasing at the college level. In a comparison of two psychology undergraduate cohorts, 1992 and 2002, they found significant reductions in mathematical competencies for all six of the components that they measured (calculation, graphical interpretation, algebraic reasoning, probability and sampling, proportionality and ratio, and estimation). This finding is important because research consistently underscores the relationship between mathematical skills and performance in statistics courses (e.g., Elmore & Vasu, 1980; Elmore & Vasu, 1986; Feinberg & Halperin, 1978; Schutz et al., 1998; Woehlke & Leitner, 1980).

Although some researchers paint a less than stellar picture of mathematics, and in particular, statistical literacy and learning at the post-secondary level, the GAISE project (ASA, 2005) is much more optimistic. It noted that the number of students taking advanced

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placement (AP) statistics has grown from 7,500 in 1997 to over 65,000 in 2004. They also report that enrollments in introductory statistics courses on the community college level have increased substantially. Mills (2004a) examined student attitudes towards statistics with the *Survey of Attitudes Toward Statistics* (SATS: Schau, Stevens, Dauphinee, & Del Vecchio, 1995). She administered the survey to 203 undergraduate psychology students and found that their attitudes tended to be more positive than negative in relation to statistics. Students agreed with items such as, "I like statistics" and "Statistics should be a part of my professional training" and disagreed with items such as "I feel insecure when I have to do statistics problems" (2004a, p. 361). She credited the statistics education reform movement for improved student attitudes towards statistics.

Although there is some positive news at the college level regarding statistics education, the GAISE (ASA, 2005) project introduced an important caveat. Current statistics students exhibited great variability in quantitative abilities and motivational levels. Consequently, statistics instructors need to begin developing strategies to address the increasing diversity among statistics students. Schutz et al. (1998) recommended the use of pre-tests to identify potential at-risk students. With proper identification, students may receive remedial assistance related to math competencies and assistance in developing highly effective, alternative learning strategies aimed at increased understanding of statistics as well as other content in other courses. This early work can help establish and build feelings of confidence and self-efficacy leading to greater motivation in the course. Schutz et al. also found that individuals of different ability levels working together during the course helps all achieve a higher level of performance.

Cognitive ability and learning styles

Researchers have also studied levels of cognitive ability and learning styles in relation to learning statistics. For example, Hudak and Anderson (1990) examined the hypothesis that students operating below Piaget's level of formal operations would have more difficulty learning and conceptualizing statistical methods. At the beginning of the semester, they tested students in both statistics and computer science classes for level of cognitive ability using the Formal Operational Reasoning Test (FORT: Roberge & Flexer, 1982) by comparing final course grades to performance on the FORT. They discovered a positive correlation between formal operational reasoning ability and successful course performance for both statistics and computer science students.

Hudak and Anderson (1990) also tested learning styles, specifically concrete experience and abstract conceptualization using Kolb's (as cited in Hudak & Anderson) Learning Style Inventory. They found that both sets of students exhibiting a high level of abstract conceptualization skills performed better than did students reliant on a high level of concrete experience. Forsyth (1977) also found students differed on measures of cognitive ability, most notably the factors related to Guilford's (1959) defined categories of memory, intellectual ability, divergent thinking, and convergent thinking. Forsyth found lower performance on each measure was associated directly with poorer performance in a statistics and research methods course.

Teachers may need to provide some students with concrete learning experiences to facilitate understanding of statistical concepts particularly as those concepts increase in difficulty. Involving students in direct experimentation and data collection is one potentially effective method for providing students such concrete experience.

Self-efficacy and motivation

Levels of self-efficacy and motivation also differ among students, potentially having a significant impact on their course performance. For example, Lane, Hall, and Lane (2004) studied the relationship between performance in a statistics class and self-efficacy. They measured self-efficacy using the Self-efficacy Towards Statistics Questionnaire (STSQ; Lane, Hall, & Lane, 2002) at the beginning and the middle of the course. The researchers found a positive correlation between self-efficacy and final performance in the class, particularly the mid-course measure. They recommended that teachers use the STSQ to identify students at the beginning of the course who may be at risk of poor performance due to low self-efficacy.

Mills (2004a) found a relationship between high statistical self-efficacy and positive attitudes about learning statistics. Of course, students may have a low level of self-efficacy based on their realistic self-assessment of their mathematical skills. As such, a math pre-test in addition to the STSQ may be beneficial in isolating the source of low self-efficacy. Lane et al. (2004) also recommended that instructors gradually provide the means for students to establish an adequate level of statistical competency early the course. Such shaping of statistical competency would simultaneously enhance student's confidence in their abilities. As part of this process, Lane et al. encouraged instructors to design the course to first increase student interest in statistics before attempting to teach highly complex tasks that might threaten students' self-efficacy.

Student motivation is also an important factor to consider in teaching the course. For example, Harris (1974) met individually with students who performed poorly (received a grade of D or F) in a statistics course. Harris found that students' low performance resulted from several factors ranging from failing to understand a major concept to lack of studying and missed classes. He continued to work with students the following semester and concluded that motivational factors played a significant role in the majority of the students' poor experiences. Harris used group review sessions to address these motivational issues rather than individual tutoring sessions. At retesting, the majority of the students passed the class.

Schutz et al. (1998) systematically studied the role of motivation in relation to performance in a statistic course. They broadly defined motivation using the learning beliefs, elaboration, and test anxiety scales of the Motivated Strategies for Learning Questionnaire (MSLQ: Pintrich, Smith, Garcia, & McKeachie, 1991) and included whether students spent additional time using alternative learning strategies such as relating the material studied to other coursework, visualization, and the development of analogies. The results confirmed earlier findings (e.g., Elmore & Vasu, 1986; Feinberg & Halperin, 1978; Presley & Huberty 1988; Woehike & Leitner, 1980) demonstrating that students with higher pre-statistics mathematical abilities performed better than did students with lower math and statistics prescores. However, Schulz et al. found some students with low pre-test scores who were successful in learning statistics. The major difference between the two groups of students with low pre-test scores was motivation and effort. Students who performed well in statistics regardless of whether they had prior knowledge of math and statistics used very different learning strategies than those students who did not do well in the course. Those who performed well used the traditional methods of reading, highlighting, memorization, and working sample problems. However, they also sought out tutoring, read other textbooks related to statistics, completed programmed instructional texts, used visualization, rewrote notes into their own words, and engaged in regular daily studying. Students who preformed poorly in the class used the traditional studying methods but did nothing more. They reported feeling more overwhelmed and lost in the course. These students relied heavily, if not solely, on rehearsal and repetition strategies, highly unproductive strategies when aimed at learning to "know how" (Evans, 1976).

Tremblay et al. (2000), extended the socio-educational model of Lalonde and Gardner (1993), and examined the role of motivation in statistics learning. Tremblay et al. defined motivational intensity as "the amount of effort students expend in learning statistics" (2000, p. 43). They found a positive correlation among motivational intensity, final exam performance, and students' positive attitudes towards the teacher. Although a correlational design, these results highlight the potential role that teachers may play in students' motivation and the importance of factors such as listening, humor, and student–teacher rapport.

Gender

Some researchers have pondered whether there is a gender difference related to learning statistics. Although Mulhern and Wylie (2004) found that men performed significantly better on a series of tests of mathematical abilities, Brooks (1987) found women had higher overall grades than did male students over the previous decade of his course. Similarly, Elmore and Vasu (1986), in a study of 188 students enrolled in a statistics class, found that women performed at a significantly higher level than did their male counterparts. However, Buck (1985) in an analysis of 13 semesters of both introductory and advanced undergraduate statistics course grades, found no gender differences related to performance in a statistics course.

In a meta-analysis of 13 articles, Schram (1996) examined the relationship of gender to performance in a statistics class, and determined that when the evaluation criterion was an exam, men performed better than did women. However, when the evaluation criterion was the total overall performance in the course, women outperformed men. In relation to attitudes, Mills (2004a), in her study of 203 undergraduate statistics students, found that women had more negative attitudes towards statistics than did men.

The question of whether gender differences exist in mathematical ability is a hotly contested issue. For example, Dr. Lawrence H. Summers, President of Harvard University from 2001–2006, initiated a maelstrom of controversy when he suggested at the National Bureau of Economic Research Conference on Diversifying the Science and Engineering Workforce that gender differences in math and science were primarily due to genetics (Summers, 2005). On the other hand, Spencer, Steele, and Quinn (1999) asserted that math differences between men and women largely result from stereotype threat versus genetically rooted sex differences. Subsequent studies have confirmed the role of stereotype threat as one explanation for gender differences in mathematics (e.g., Martens, Johns, Greenberg, & Schimel, 2006; Marx & Roman, 2002; McIntyre, Paulson, & Lord, 2003; O'Brien & Crandall, 2003). Although the question of gender differences in mathematics is still unresolved, it is likely that the issue is much more complex than simply who gets the highest grade at the end of the term.

Helping Your Students Survive Statistics

There are many ways that teachers can help their students survive and even thrive as they make their way through a semester of introductory statistics. Given the tendency for math anxiety to drives students' perceptions of statistics, instructors should assure students that statistics is not primarily a math class. Indeed, as noted by the GAISE Project (ASA, 2005), it is important to foster conceptual understanding as opposed to simply procedural understanding of the material. Nonetheless, a look of panic on students' faces at the first glimpse of a formula or a table practically assures that conceptual learning will be lost given the negative correlation between learning and statistics anxiety (Lalonde & Gardner, 1993; Onwuegbuzie & Seaman, 1995; Onwuegbuzie & Wilson, 2003; Tremblay et al., 2000; Zanakis & Valenza, 1997; Zeidner, 1991). Consequently, teachers must incorporate strategies aimed at reducing math anxiety and enhancing self-efficacy in the course structure from the first day of class. We will discuss strategies aimed at reducing statistics anxiety and increasing self-efficacy in greater depth in Chapter 4.

Instructors can also teach students to self-monitor their learning process during the course. For example, Lan (1996) tested the effects of self-monitoring on class performance. Lan assigned students to one of three groups: self-monitoring, instructor-monitoring, and control. Students in the self-monitoring group kept a daily log documenting the time they spent using various learning strategies (e.g., group discussion, tutoring, problem solving), the amount of time they spent studying a particular statistical concept, and they recorded their confidence level in understanding the material. Students in the instructor monitoring condition had the same list of statistical concepts but evaluated the instructor's teaching. Lan found that students in the self-monitoring group performed at a significantly higher level than the other two groups and demonstrated a better ability to organize and understand course content. Relative to the other two groups, the self-monitoring group also engaged in a higher number of self-regulatory learning strategies such as environmental structuring, review of previous work, and self-evaluation. However, Lan noted that students' self-regulatory behavior declined when they faced complex learning tasks, particularly when those tasks required an increased focus on the processing of the new information. Lan found no difference in motivation levels among the groups, suggesting that the self-monitoring was equally beneficial for all students.

In some small measure, encouraging self-monitoring behavior facilitates students' use of good study habits. Hastings (1982) and Schutz et al. (1998) stressed the importance of good study habits and keeping up with the material. Students who self-monitor may be quicker to realize that they are in need of tutoring, including peer tutoring, both of which can be beneficial for students in statistics courses (Conners, Mccown, & Roskos-Ewoldsen, 1998; Ward, 1984). In addition, students and instructors can use self-monitoring to recognize the warning signs of future trouble and as a guide to adopt new learning strategies or seek assistance.

Finally, students' motivation increases when they recognize the practical benefits of a course. Students entering graduate school with weak statistical and methodological training are at greater risk for dropping out than well-prepared students (Jannarone, 1986). Clough (1993) argued that employers expect that potential employees with undergraduate psychology training have skills in both statistics and methodology. Unfortunately, alumni do not appear to recognize the benefit of these skills, or perhaps, that they even have these skills (Grocer & Kohout, 1997).

If students avoid quantitative methods coursework and view it as having little relevance, then such biases will most likely shape and limit their future career choices as well. Exposing students to exciting careers possibilities that require knowledge of methodology and statistics can help reverse this trend. For example, Beins (1985) described a statistics class project whereby students contacted companies and requested data related to studies mentioned in advertising claims. Through such creative projects, students can discover that statistics have real world usefulness and context. With greater emphasis on the opportunities available to students with a background in quantitative methods, students will begin to incorporate such ideas into their own thinking, studying, and potential career opportunities.

Conclusion

Statistics can be a challenging, engaging, and positive educational experience for students. However, to realize this potential, instructors need to pay particular attention to the design of the course to maximize the learning experience. Specifically, instructors need to attend to a host of details from selection of teaching strategies aimed at anxiety reduction to the selection of activities designed to maximize the development and assessment of students' statistical literacy, thinking, and reasoning skills. To make informed choices about the best methods to teaching statistics, instructors need to be familiar with the growing literature on statistics education. Ideally, the journey through statistics is much like a well-planned, but oft repeated, road trip. The route remains relatively the same but the company and process of exploration are dynamic and interactive with each journey. Thus, the trip is never dull.