Techniques in Teaching Statistics: Linking Research Production and Research Use

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ABSTRACT
In the spirit of closing the “research-practice gap,” the authors extend evidence-based principles to statistics instruction in social science graduate education. The authors employ a Delphi method to survey experienced statistics instructors to identify teaching techniques to overcome the challenges inherent in teaching statistics to students enrolled in practitioner-oriented master’s degree programs. Among the teaching techniques identified as essential are using real-life examples, requiring data collection exercises, and emphasizing interpretation rather than results. Building on existing research, preliminary interviews, and the findings from the study, the authors develop a model describing antecedents to the strength of the link between research and practice.

We want to motivate students on two fronts: first, to seek research findings related to the problems they address, and second, to use the results of their research as an important guide for their actions and decisions. (Fitzpatrick, 2000, p. 174)

The ability to employ and comprehend statistical concepts and tools is an essential skill in managerial activities. In the last 50 years, efforts to collect, analyze, and use data to improve performance have been on the rise (Julnes, 2007). Moreover, with advances in information technology, the need for
quantitatively trained personnel will continue to grow (Colwell & Kelly, 1999; Dawes, 2004; de Libero, 2005; Lane, Mansour, & Harpell, 1993; Philip & Shultz, 1994; Vijverberg, 1997). Traditional methods of teaching introductory statistics courses are often viewed as ineffective (Peiris, 2002; Schacht & Aspelmeier, 2005; Yilmaz, 1996; Zanakis & Valenzi, 1997), resulting in student anxiety about coursework, a perception that statistics is too difficult, and failure to persuade students that statistics is relevant to their careers (Davis, 2003; Forte, 1995; Zanakis & Valenzi, 1997). Thus, although statistics is commonly necessary in real-world work, there is a perceived gap between research and practice (Shapiro, Kirkman, & Courtney, 2007). Ultimately, practitioners remain quantitatively underprepared for their jobs.

The existence of a gap between research and practice means that practitioners are not using research that might assist them in making better decisions, and researchers may not be producing high-quality research that has relevance for practitioners (Adams & White, 1994; Calderwood, 2002; Duncan, 1974; Felbinger, Holzer, & White, 1999; Fitzpatrick, 2000; Mosher, 1975; Pfeffer & Fong, 2002; Rousseau, 2006; Rousseau & McCarthy, 2007; Rynes, Bartunek, & Daft, 2001; Shapiro et al., 2007). There has been an effort to understand researcher-practitioner collaboration (Amabile et al., 2001) and influence ways to generate research and knowledge that is useful in practice (Mohrman, Gibson, & Mohrman, 2001; Van de Ven & Johnson, 2006). However, it seems that, “much of the knowledge taught does not make its way out of the classroom and much of the knowledge discovered does not make its way beyond the handful of academics who share the same research interests” (Blood, 2006, p. 210). Furthermore, “the impact that management research has (or doesn’t have) on private and public sector managerial practice is a topic of ongoing debate” (Shapiro et al., 2007, p. 249).

As shown in Figure 1, research production and research use interact iteratively, informing and changing each other through a reinforcing feedback process (the production-consumption loop, indicated by R1 in Figure 1) with the potential to meaningfully influence public and private policy outcomes (Ouchi, 2003). We hypothesize that more high-quality and relevant research leads to more use of this research by practitioners. In turn, the use of research influences the creation of more research with high quality and relevance, creating an ongoing cycle of research production and use. Certainly, if researchers are not producing relevant research, practitioners will not use it. When practitioners’ use of research declines, researchers’ potential to produce relevant research diminishes, leading to a decline in quantity, quality, and relevance of research output. In the research production-consumption cycle, producers inform consumers and consumers, in turn, inform producers through a feedback process with the potential to create both successful and failing research production-consumption patterns.
Many researchers have explored the antecedents of the production of relevant and high-quality research, investigating such issues as the types of research done in PhD programs (McCurdy & Cleary, 1984; White, 1986), methodological and quantitative rigor in published research (Box, 1992; Houston & Delevan, 1990; Perry & Kraemer, 1986; Stallings & Ferris, 1988; Vijverberg, 1997; Wright, Manigault, & Black, 2004), and quantitative training in doctoral programs (Brewer, Facer, O’Toole Jr., & Douglas, 1998; Rethemeyer & Helbig, 2005). This paper builds on the work of Desai (2008) and Mandell (2008) and explores the other side of the process by examining one of the antecedents that influence the extent to which research is used in practice: the development of quantitative (specifically statistical) skills to understand and use research findings. The production-consumption of the research cycle captures the essence of what Rousseau (2006) terms “evidence-based management” (see also Rousseau &

Figure 1.
Model of Research Production and Research Use

![Model of Research Production and Research Use](image)

Arrows indicate the direction of causality between variables. Signs (+ and –) indicate the polarity of the relationship. A + sign means that, all else equal, increases in the variable at the beginning of the arrow will result in increases in the variable at the end of the arrow. Similarly, a – sign means that, all else equal, increases in the variable at the beginning of the arrow will result in decreases in the variable at the end of the arrow.

Reinforcing loop polarity (denoted by R in the loop identifier) indicates the existence of a self-reinforcing (also called positive) feedback process.
McCarthy, 2007; Sanderson, 2002). The extent and adequacy of research use depends on the existence of both (a) high-quality research that is relevant for practice and (b) adequate quantitative skills to understand and use such research (e.g., statistical knowledge). Our goal is to identify and describe techniques used by experienced statistics instructors to address challenges inherent in teaching statistics in practitioner-oriented master’s degree programs.

Problems managers face are messy and ill defined (Ackoff, 1974; Churchman, 1967; Conklin, 2006; Horn, 2001; Rittel & Webber, 1973). When faced with a task or problem, practitioners need to be able to think critically, distinguish what is relevant from what is not, consider facts and relationships, systematically uncover alternatives, determine the effectiveness of programs and projects, use persuasive reasoning to support claims, and use data to inform decisions (Desai, 2008; Hill & Lynn, 2009; Hodges, 1996; Toulmin, 1964; Williams, Colomb, D’Errico, & Tracey, 2003). Thus, the ability to effectively explore existing theories and empirical research on what other practitioners and researchers have done or considered in similar situations is critical (Fitzpatrick, 2000; Meier, Brudney, & Bohte, 2006; Van de Ven & Johnson, 2006).

However, practitioners do not always make decisions informed by research and evidence (Desai, 2008; Rousseau, 2006). What can we do to make practitioners better consumers of research? This paper explores one possible answer to this question—namely, to help instructors develop the tools and skills they need to grow “reflective practitioners” (Davenport & Markus, 1999; Rousseau, 2006, p. 20). While high-quality empirical research takes many forms, this project focuses only on quantitative, in particular, statistical empirical research.

In this project, we identified the challenges facing statistics instructors and some of the practices for addressing these challenges. We employed a sample of experienced statistics instructors in the social sciences to identify the tools and techniques that are most effective in addressing the challenges inherent in teaching statistics to students enrolled in practitioner-oriented master’s degree programs. We distinguish practitioner-oriented master’s programs from other master’s degree programs in that individuals attending such programs are nonspecialists in the field of statistics. Students of this type of program tend to be consumers, rather than producers, of statistical research.

This paper is divided into five sections. The first section reviews literature relevant to teaching statistics and discusses the use of the Delphi technique as a research method. The second section describes the data collection techniques and the methods used to analyze the data. The third section presents findings, implications, and discussion of our analysis. The fourth section describes an extended version of the model presented in Figure 1 of the introduction. The paper concludes with a discussion including limitations, contributions, and directions for future research.
LITERATURE REVIEW

Because students often experience anxiety, a sense of intimidation, and lack of motivation when faced with statistics, such courses can be among the most challenging to teach—often resulting in similar emotional reactions for instructors (Calderwood, 2002; Forte, 1995; Schacht & Aspelmeier, 2005). Traditional statistics education has focused on the knowledge and skills components of learning or on the logical and physical aspects of understanding statistics, assuming that the desire to learn statistics or the mitigation of the emotional aspects will follow the acquisition of these skills.

The emotional aspects represent the perceived value of statistics to students; they will engage themselves in statistics only if they see value in it (Calderwood, 2002; Snee, 1993; Zanakis & Valenzi, 1997). In past years, scholars have found evidence to suggest that students do not see the value in statistics. For example, even after students took a statistics course, Zanakis and Valenzi (1997) found that their interest in the subject and perceived worth of the subject declined. Jordan and Stroup (1984) suggested that although taking a statistics course may have resulted in a reduction in student fear of the course, it did little to persuade students of its value in the real world. Swanson, Meinert, and Swanson (1994) found that, compared with other core courses in a business curriculum, students perceive statistics to have little practical value, to be very difficult, and to have only average instructional effectiveness.

In addition to past evidence of the perception that statistics has limited value, there is also evidence to suggest that students experience high anxiety about the course due to their lack of understanding of statistics, the fact that they are required to take tests in the subject, and their limited experience with using computer software for statistical calculations (Zanakis & Valenzi, 1997). It is noted, however, that in the most recent decade, computer usage has increased substantially both in education settings and in general life activities. Thus, general computer literacy might not represent an obstacle now; but students quite likely may continue to be unfamiliar with statistical software such as SPSS, STATA, or SAS. Even students who are comfortable with using a familiar software package such as Microsoft Excel for tasks like keeping track of information may be quite unfamiliar with the data analysis tools and statistical functions in this software program (formulas and mathematical functions, histograms, regression analysis, etc.). Math anxiety, lack of experience with specialized statistics software, perceived difficulty of the subject matter, and the assumption that statistics is not a valuable career or life skill can translate into student apprehension and lack of focus, instructor frustration, and, ultimately, a negative learning environment (Schacht & Aspelmeier, 2005).
A variety of strategies have been proposed to address these issues. In general, these strategies can be grouped into three primary categories: teaching techniques, course content revision, and pre-course training. These categories are described next.

**Teaching Techniques**

Many have proposed specific teaching techniques or tools to address challenges inherent in teaching statistics. For example, experiential learning has been suggested as a technique for building student beliefs that statistics is valuable, reducing test anxiety for students, and integrating statistics into the lives of students—thus increasing its perceived value (Cobb, 1991; Snee, 1993; Zanakis & Valenzi, 1997). Experiential learning in statistics involves working with real data, solving real problems, and improving real processes (Calderwood, 2002; Snee, 1993). Strasser and Ozgur (1995) suggest the use of case studies, a technique similar to experiential learning.

In teaching statistics to social and behavioral science students, humor is favored by instructors as a tool for overcoming math anxiety. Schacht and Aspelmeier (2005) and Forte (1995) use cartoons to reduce student anxiety about math and statistics. These authors contend that students suffering from math anxiety tend to keep these feelings secret and thus avoid seeking help from the instructor or classmates. This can lead to student failure as well as instructor perception that students are lazy or unprepared. Humor and laughter can be used to acknowledge feelings of math anxiety in students and reduce tension.

Others have suggested applying statistics to current events by using newspaper articles and other news sources as a way to persuade students that statistics may be valuable in their careers and lives (Peiris, 2002; Strasser & Ozgur, 1995; Zanakis & Valenzi, 1997; Calderwood, 2002). For example, if the government claims in a newspaper article that the unemployment rate is 7% and an opposing group claims otherwise, showing students how this dispute can be resolved by using statistics will help persuade them that statistics does, in fact, have real-life value (Peiris, 2002).

For others, making statistics memorable, exciting, and more fun are also ways to increase student interest in, and perceived value of, the subject (Sowey, 1995; Strasser & Ozgur, 1995). Instructor excitement about course materials will affect students in positive ways. When an instructor is passionate about course material, it is easy for students to become excited as well.

Students have many different thinking and learning styles. Kolb and Kolb (2005) assert that the way individuals learn, which is influenced by such factors as personality type, education specialization, career choice, and current job role and tasks, shapes the course of their personal development and learning styles. Snee (1993) suggests incorporating a variety of learning methods into the statistics curriculum to accommodate a range of learning styles. While some students learn best by reading books and listening to lectures, others learn...
best by engaging in exercises, writing summaries, and taking part in material review sessions. Still others prefer visual aids, metaphors, and experiments. Incorporating a variety of these tools into a statistics curriculum will allow instructors to reach students in the ways that they learn best.

On the basis of the six components of statistics anxiety (Cruise, Cash, & Bolton, 1985), Davis (2003) suggests that instructors begin their statistics courses with a discussion of statistics anxiety. This discussion should include literature on the subject and a chance for students to voice their concerns. The open dialogue acknowledges that statistics anxiety is real and lets students know that the instructor takes their concerns seriously.

In addition to the teaching techniques already described, other recommendations for addressing challenges that instructors face in teaching statistics courses include the following: dividing classes into small collaborative groups (Calderwood, 2002; Davis, 2003; Forte, 1995; Peiris, 2002; Zanakis & Valenzi, 1997); incorporating greater use of computer technologies, especially those that are in demand in the market (Forte, 1995; Peiris, 2002; Strasser & Ozgur, 1995); providing lecture notes and study aids (Davis, 2003); and periodically holding class in the computer lab to facilitate software usage (Forte, 1995).

Course Content Modifications

Beyond specific teaching techniques, others recommend changing the content of statistics courses to address some of the challenges facing statistics instructors. Examples of such changes include reducing methodology coverage (Zanakis & Valenzi, 1997), weighting tests less or modifying grading techniques (Calderwood, 2002; Zanakis & Valenzi, 1997), improving textbooks (Schacht & Aspelmeier, 2005; Sowey, 1995; Strasser & Ozgur, 1995), going into greater depth on fewer topics (such as research design, data collection, and data display; Fitzpatrick, 2000; Snee, 1993; Strasser & Ozgur, 1995), and reducing coverage of such topics as hypothesis testing, probability, and mathematical concepts (Desai, 2008; Snee, 1993; Strasser & Ozgur, 1995). Conversely, Strasser and Ozgur (1995) also report that some instructors wish that more topics were covered.

Fitzpatrick (2000) argues that, to become better consumers of research, students must not only understand statistics, but they must also understand how to read existing literature. Thus, course content should include a research-consumption component that teaches students to read and interpret literature reviews, data and methods, findings, and implications of existing research throughout the course. Calderwood (2002) suggests changing the titles of statistics courses to be more relevant and less intimidating. Students should understand that the purpose of the course is not to transform them into statisticians or mathematicians, but rather to teach them basic statistical concepts and tools and the appropriate ways to use these concepts and tools in data analysis processes.
Pre-Course Training

In addition to specific teaching techniques and modifications of course content, some instructors suggest that student anxiety and frustration could be reduced with changes in pre-course training. Anxiety experienced by students and frustration experienced by instructors is in part related to the students’ lack of specific computing skills (Strasser & Ozgur, 1995; Zanakis & Valenzi, 1997). Some instructors advocate requiring that students take a microcomputer technology and computer literacy course before they can take a statistics course. Others suggest that students be required to take more than one statistics course (Strasser & Ozgur, 1995), allowing instructors more time to cover complicated topics. This approach would help ensure that by the time students begin the second statistics course, their anxiety will have decreased, and their skill set will have increased. One other recommendation is that statistics be part of a two-course sequence: students would start by taking a course covering the basics of research design and then would move on to a statistics course (Forte, 1995).

The valuable recommendations provided in the literature are generally based on the individual personal experiences of instructors. Thus, these recommendations have the advantage of being authentic in that they are based on personal anecdotes and actual experiences. One way to build on this literature is to base recommendations for teaching statistics on what can be gleaned from an aggregation of personal experiences from several, or even many, individuals. Continuing the work of Strasser and Ozgur (1995), who surveyed statistics instructors about what they “wish” for in a statistics course; Davis (2003), who undertook a case study to measure student statistics anxiety before and after taking a specially designed statistics course; and Mandell (2008), who surveyed a group of academic instructors in public policy analysis and management programs, we employ a systematic approach using a Delphi technique to identify a set of tools and techniques to teach statistics to practitioners based on the aggregation of the experiences and wisdom of several individuals.

The Delphi Method

As suggested earlier, teaching statistics to nonspecialists poses many challenges (Yilmaz, 1996). While a variety of methods have been suggested for addressing these challenges, the list of recommendations is lengthy and relies primarily on individual experiences and opinions. One way to further the valuable contributions garnered from these experiences is to use a Delphi technique to identify a set of tools and techniques that experienced instructors use to teach statistics to individuals enrolled in practitioner-oriented master’s degree programs. By using a Delphi technique, we can discern which practices are suggested by one and which practices are suggested by many. In other words, we can identify a set of tools and techniques that is based on an aggregation of personal experiences from several statistics instructors.

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The Delphi method is particularly suited for this study. This technique will help identify the common tools and techniques instructors use to teach statistics in practitioner-oriented master’s degree programs. The Delphi technique allows participants to respond to questions in two or more rounds. After each round, the facilitator provides an anonymous summary of the participants’ answers to the round of questions and allows each participant to revise his or her original answers based on the other answers provided by the rest of the respondents (Alder & Ziglio, 1996; Linstone & Turoff, 1975).

The Delphi technique has allowed researchers to produce insights in an area where direct observation was not possible (Dalkey & Helmer, 1963), has been more effective in producing a large number of ideas than other group processes (Van de Ven & Delbecq, 1974), reduced respondent bias because of the anonymity provided during data collection (Williams & Webb, 1994), and helped scholars distinguish between what is essential versus what is simply important (Smith & Simpson, 1995). This technique has been used by a number of scholars to gain consensus on things such as teaching competencies in higher education (Smith & Simpson, 1995; Tigelaar, Dolmans, Wolthagen, & Vleuten, 2004; Williams & Webb, 1994) and management competencies in local government (Lazenby, 2010).

This paper addresses three primary opportunities not specifically addressed in the literature. First, when considering the link between research and practice, most existing research addresses antecedents to the production of useful research, primarily doctoral education. This paper addresses one of the antecedents to effective consumption of this research. Second, in uncovering the tools and techniques most appropriate for addressing the challenges of teaching statistics, most recommendations are based on anecdotal evidence or case studies. For this project, we systematically collected data from a group of statistics instructors, identifying areas of agreement and disagreement about such tools and techniques. Third, in identifying tools and techniques to address challenges facing statistics instructors, the electronic Delphi technique has been left largely unexplored; this paper employs this approach.

**Data and Method**

As suggested earlier, the general goal of this paper is to identify and describe practices used by experienced statistics instructors to address the challenges inherent in teaching statistics in a practitioner-oriented master’s degree program. Thus, our research was conducted in four phases. First, we identified common challenges faced by statistics instructors. Second, we established a sample of experienced statistics instructors. Third, we collected data from our sample respondents through a Web-based discussion tool using an electronic Delphi technique (Turoff & Hiltz, 1982). Finally, we analyzed the data collected and used the findings to develop a model. The details associated with each phase are described here.
Phase I: Identification of Common Challenges

Based on literature (Schacht & Aspelmeier, 2005; Yilmaz, 1996) and interviews with three university faculty members who teach statistics in two master’s-level social science disciplines, we identified four general areas of challenge faced by statistics instructors.

1. Designing and selecting tools effective for learning is difficult.
2. Students tend to have a low level of and/or limited background in quantitative skills.
3. Students tend to want to memorize statistics rather than understand its underlying concepts.
4. Students tend to have low levels of motivation, participation, and engagement with the subject matter of statistics.

After defining these challenges, we formulated one survey question per challenge to help identify the tools and techniques used to address each challenge. For example, the question used to elicit ideas for addressing challenge 3 was, “If you were offering advice on the best way to teach statistics to students in practitioner-oriented master’s degree programs, what activities would you say are essential for addressing students’ tendency to want to memorize instead of understand?” Participants were asked a total of four questions, one question to address each of the challenges identified above. The four questions asked to participants are included in Appendix A.

Phase II: Sample Selection

Using a purposive sampling method (Bernard, 2000), we identified several group characteristics for our participants. First, we wanted the participants to be experienced faculty members teaching in practitioner-oriented master’s degree programs. The idea here is, in thinking about teaching techniques that are effective, instructors need to have sufficient time (i.e., semesters taught) to develop teaching practices and experiences. In addition, teaching statistics in practitioner-oriented master’s degree programs where students are more likely to be consumers of statistics rather than producers presents unique challenges that may be different from the challenges in teaching statistics in other types of master’s degree programs. For example, teaching statistics to master’s students in a public affairs program might be different than teaching statistics to master’s students enrolled in economics or computer science. Second, we wanted a participant group of approximately 20. Using an electronic Delphi technique to gather data requires a moderately small group for logistical purposes. A group with too many participants could generate a list of initial ideas that would be unmanageably large for the group to review and revise. Third, we wanted participants who were interested in discussing teaching techniques. We cast a wide net for participants, knowing that those who agreed to participate were
likely very interested in the subject of our study. Thus, we were willing to accept the self-selection bias that may result.

To begin identifying our sample, we selected the top 10 graduate schools between 2003 and 2005, as ranked by *U.S. News and World Report* (2005, 2006), in six social science disciplines containing practitioner-oriented master’s degree programs: business administration, criminology, higher education administration, public affairs, public health, and social work. While these six social science disciplines have many differences, discussions with instructors teaching statistics in these types of programs suggest there are commonalities in the challenges instructors face in teaching statistics to students across such programs. We acknowledge that a top ranking does not necessarily ensure high-quality teaching as well. This listing was used as a method for identifying a manageable sampling frame that would contain participants meeting our desired group characteristics.

Using the top-ranked schools in these six disciplines resulted in a list of 66 schools. From these 66 schools, we contacted a school representative to identify who teaches statistics as well as e-mail contact information for such instructors. We removed 11 schools from the original list of 66 because they either (a) did not have a practitioner-oriented master’s degree program; (b) did not require statistics as part of the curriculum; or (c) faculty members teaching statistics were unavailable because of sabbatical, illness, or other professional duties. Of the remaining 55 schools, 34 representing each of the six disciplines originally selected responded with the names and contact information for statistics instructors in their departments. From these 34 schools, we compiled a list of 77 eligible statistics instructors and contacted each one via e-mail, informing the instructors about our project and asking them to participate. Of the 77 instructors contacted, 25 instructors were willing to participate.

The U.S. Department of Education’s National Center for Education Statistics defines “new faculty” as those in their first seven years of academic employment (U.S. Department of Education, 1998). Based on this definition, we define experienced instructors as those who have been teaching statistics for 8 or more years. After we identified “experienced” respondents, 18 instructors from 14 schools in five social science disciplines remained in our sample.

Once data collection began, of the 18 instructors in our sample, 13 actually participated in the first stage (generating ideas in response to the four questions), 8 in the second stage (clustering the ideas generated from all participants), and 7 in the third stage (prioritizing the clusters).

**Phase III: Data Collection**

Because our sample contained individuals located in a variety of time zones throughout the United States, individual interviews and/or focus groups, although feasible, were extremely difficult. Using an electronic Delphi method, we followed Rohrbaugh (2000) and Martinez-Moyano and Richardson (2002)
and employed a Web-wide participation tool. The electronic Delphi technique has several advantages. First, the facilitator controls the contributions from the participants. This reduces some of the problems associated with group dynamics, such as groupthink and leader dominance (Janis, 1972; McCauley, 1989; Wissema, 1982). Second, the anonymity of the respondents reduces the bandwagon effect (Coleman, 1973), whereby the chances of one individual in the group adopting an idea increases based on who else in the group has already adopted the idea; and the halo effect (Nisbett & Wilson, 1977), whereby the first characteristics we recognize about an individual influences our interpretation of later characteristics of that individual. Anonymity also encourages open criticism, admittance of mistakes, and revision of original stances. Finally, because the discussion tool was Web based, participants could access the tool at any time, and responses did not have to be completed in one sitting.

While there is ample variation in how the Delphi technique has been employed, the procedure used in this project was conducted in three rounds as follows: First, an idea elicitation stage in which the subjects were presented with the survey questions described in Appendix A was conducted. In this stage, the respondents generated ideas independently of one another, and the ideas generated by all respondents were aggregated in one list. Second, an idea clustering stage in which the aggregated list was returned to respondents for grouping based on similarity. A list of groups generated by respondents was created based on grouping agreement among respondents. Third, a cluster prioritizing stage in which the list of grouped ideas was independently evaluated by the respondents based on relative importance. The resulting groups and the level of agreement achieved became the primary portion of the analysis. Each stage of the Delphi procedures is discussed in detail next.

To begin the idea elicitation stage, we sent participants an e-mail with a link to the Web-wide participation meeting. The purpose of this step was to elicit ideas from participants regarding methods to address the challenges inherent in teaching statistics to students enrolled in practitioner-oriented master’s degree programs. Participants answered each of the four survey questions privately, but they were given the opportunity to view an anonymous list of answers generated by other participants as these became available. This is similar to a brainstorming exercise wherein an unlimited number of ideas can be generated. The elicitation stage lasted 3 weeks. During this time, participants generated ideas in response to each of the four questions. At the end of the session, the authors compiled an aggregated list of all the ideas produced by participants by question.

After the idea elicitation stage, we began the idea clustering stage. The purpose of this stage was to get participants to examine the aggregate list of ideas (by question for each of the four questions asked) and cluster these ideas based on similarity. There were no predetermined clusters. Participants were asked to cluster ideas that they thought were similar. Participants privately clustered
ideas for each of the four questions separately and could create an unlimited number of clusters with no restrictions on how many ideas could be assigned to a cluster. For example, if the participant thought that all the ideas belonged in one cluster, he would assign all of them to the same one. Alternatively, if the participant thought that all the ideas were distinctly different and would not belong to the same cluster, he would create as many clusters as ideas existed in the list, assigning one idea to each cluster created. All of our participants created more than one cluster and less than the total number of ideas presented to them. This stage allowed participants to narrow down the initial list of brainstormed ideas into more general clusters of practices, thus consolidating ideas into more manageable clusters. Participants were allowed 3 weeks to cluster the ideas contained in the aggregated list that they had populated in the prior stage.

Each participant generated different clusters of ideas. To identify clusters that most participants agreed on, each participant’s clusters were compared using a 70% agreement threshold and the analytic routines embedded in the Web-wide participation tool. The 70% agreement threshold indicates that the ideas in each cluster were linked to most or all of the other ideas in the cluster by at least 70% of participants. This process resulted in the identification of 19 clusters of ideas for question one, 21 clusters for question two, 21 clusters for question three, and 14 clusters for question four. The identified clusters were used in the next stage of the process: the prioritization stage.

In the prioritization stage, participants prioritize the identified clusters of ideas according to their relative importance for addressing the relevant challenge (i.e., as essential for addressing one of the listed challenges inherent in teaching statistics). This prioritization activity was intended to distill what general practices (clusters) were most important for addressing each challenge. To begin, participants were shown a list of the identified clusters. Each cluster was given a score of 100 points. Participants then increased or decreased this score based on how important they believed the cluster was for addressing the challenge described in the question. Higher scores indicated more important clusters; lower scores indicated less important clusters. For example, if a participant thought that cluster 1 was twice as important as cluster 2 in addressing the challenge under study, he would assign twice as many points to cluster 1 than those assigned to cluster 2 (either by assigning 200 points to cluster 1, or by assigning 50 points to cluster 2 without changing the original 100 points assigned to cluster 1).

Because participants used self-determined scores for indicating importance, we standardized the scores assigned by each participant following the prioritization stage in order to compare scores for a particular cluster among participants. To standardize the assigned scores, we calculated the sum of all points assigned to all clusters by a participant and then divided the score assigned to an individual cluster by this total.
Phase IV: Data Analysis

Of those participating in the study, 5 of the 13 instructors were female. These instructors represented five of the six social science disciplines in our original target group. (No instructors from business programs participated in the study.) The colleges and universities with which the responding instructors were affiliated were predominantly public (9), the largest proportion of instructors being from public affairs programs (5). On average, this group of instructors had their PhDs for over 18 years (minimum, 3 years; maximum, 36 years) and had taught statistics for over 16 years (minimum, 8 years; maximum, 31 years). During the idea elicitation stage, an average total of 41 ideas were generated for each challenge. The greater the number of ideas generated, the greater the potential for creativity in the Delphi process (Van de Ven & Delbecq, 1974). On average, for all four questions asked, participants placed more than two ideas in each cluster. The minimum number of ideas placed in a cluster was 1; the maximum was 10. These distributions were relatively right-skewed, and several clusters included only one idea.

While only 7 of the original 13 instructors participated in all stages of the Delphi process, we provide summary statistics on all 13 of the instructors here because all 13 provided the initial list of ideas deemed essential for addressing the challenges. This elicitation of ideas formed the core of the remainder of the data collection stages.

Identifying Agreement among Participants

A major goal of this project was to identify the tools and techniques that instructors agreed are essential for addressing the challenges in teaching statistics to students enrolled in practitioner-oriented master’s degree programs. Participants’ rankings of clustered ideas were divided into three groups using the mean rating for the cluster and a simple majority rule. By using the simple-majority criterion, in conjunction with the mean rating for a cluster, we address potential issues arising from the sensitivity of the mean to outliers.

The three groups created are the highest-importance group, the high-importance group, and the average-importance group. These groups capture how essential each cluster is for addressing the challenge in question. Thus, clusters in the highest-importance group are considered by the experienced instructors in our study as the most essential for addressing the challenge. Table 1 summarizes the method used to identify agreement among participants.

Findings

According to the group of experienced instructors that participated in our research, when designing and/or selecting tools effective for learning, instructors should focus on using real-life, relevant examples; employing computer applications; and emphasizing the process, not the results. Additionally, to
Table 1. 
*Downloads of Papers at Selected Educational Institutions*

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<tr>
<th>Challenge: Tools Effective for Learning</th>
<th>Highest-Importance Group</th>
<th>High-Importance Group</th>
<th>Average-Importance Group</th>
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<tbody>
<tr>
<td>• Use relevant real-life examples.</td>
<td>• Use simulation to generate insights about statistical concepts.</td>
<td>• Focus on restructuring how students think.</td>
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<tr>
<td>• Employ computer applications.</td>
<td>• Emphasize the process, not the results.</td>
<td>• Do easy math.</td>
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<tr>
<td>• Emphasize the process, not the results.</td>
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<td>• Use notation early.</td>
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<th>Challenge: Low Levels of Quantitative Skills</th>
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<td>• Apply statistics to real life.</td>
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<td>• Require data collection exercises.</td>
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<th>Challenge: Desire to Memorize Rather than Understand</th>
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<td>• Select an appropriate text.</td>
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<td>• Use relevant examples.</td>
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<td>• Select textbooks that employ practical examples.</td>
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<td>• Use “story” problems.</td>
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<th>Challenge: Low Levels of Motivation, Participation, and Engagement</th>
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<td>• Use relevant examples and require students to do the same.</td>
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<td>• Provide examples of bad use of statistics.</td>
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address the quantitative underpreparedness and math anxiety of students, instructors should focus on applying statistics to real life and require students to engage in actual data collection. To tackle students’ desire to memorize rather than understand, instructors should use relevant examples, select textbooks that are appropriate and employ practical examples, and use “story” problems. To deal with low levels of motivation, participation, and engagement among students, instructors should be sure to emphasize interpretation and understanding, not results; build knowledge incrementally; and allow memorization.

In a general sense, instructors should focus on four macro categories of tools and philosophies when trying to address each of the challenges associated with statistics education emerge (Figure 2): use of relevant real-life applications, use of technology, focus on process and understanding, and student-centric considerations. Additionally, seven pieces of advice for instructors can be garnered from the four macro categories.

**Advice for Statistics Instructors: Insights to Take into the Classroom**

1. Use topical examples from current events and practitioner sources and very clearly illuminate how statistics relates to these examples of real life. (Macro category: Use of relevant real-life applications)

The emphasis on using concrete examples of applied statistics was the most common suggestion among instructors participating in the Delphi exercise. It was clear that these real-life examples were not only advisable, but an absolute necessity. These examples should come from sources familiar to the students, sources they encounter in their lives—or, as more succinctly stressed by one participant, “from practitioner sources, not journals.” Another participant suggested working with the same articles and readings that the students are simultaneously using in other courses. To illustrate how statistics relates to real life, one instructor said, “Elaborate the client’s stories behind the statistics.” In addition to other common suggestions such as using assignments that require analyzing statistics in current events, many instructors also suggested having students conduct an original data analysis exercise. Some suggested that students design a study, collect a small amount of original data on a topic of interest to them (related either to an academic program or an outside interest), conduct the analysis, and write up the results. Others suggested employing the help of other faculty to “engage [students] in a real world project in an area of interest to them.” Finally, selecting an appropriate textbook that uses relevant examples was also discussed as paramount.

2. Use computer applications early and often, but not without conceptual explanation. (Macro category: Use of technology)

One theme that received overwhelming attention among experienced instructors teaching statistics in practitioner-oriented master’s degree programs was the use of statistical software by students. This is considered essential, and
Figure 2. Expanded Model of Research Production and Research Use

Techniques in Teaching Statistics

Use of Technology
- Apply statistics to real life [Ch 2]
- Use relevant examples [Ch 1]
- Use “story” problems [Ch 3]
- Select textbooks that employ practical examples [Ch 3]
- Select an appropriate text [Ch 3]
- Employ computer applications [Ch 1]
- Use simulation to generate insights about statistical concepts [Ch 1]
- Utilize online discussion groups [Ch 3]

Focus on Process and Understanding
- [Ch 1] Designing and/or selecting tools effective for learning
- [Ch 2] Deal with low levels of motivation, participation, and engagement of students
- [Ch 3] Neutralize tendency to want to memorize instead of understand
- [Ch 4] Overcome quantitative underpreparedness and math anxiety of students

Student-centric Considerations
- Ignore lack of motivation [Ch 2]
- Allow memorization [Ch 4]
- Provide examples of bad use of statistics [Ch 4]
- Reiterate the same problems using different techniques [Ch 3]
- Do easy math [Ch 1]
- Use notation early [Ch 1]
- Require data collection exercises [Ch 1]
- Require data collection exercises [Ch 1]
- Demonstrate the value of understanding statistics [Ch 1]
there is a consensus that students should get accustomed to it. Students should see examples performed in class using software and be required to engage in some hands-on use of statistical software as well. One participant said, “Spreadsheet software and a projection system for in-class examples—essential!” However, along with the software, students must also get conceptual explanations. Aply put by one participant, instructors should “avoid statistical ‘packages’ as ‘black boxes’ (numbers in, numbers out).”

In addition to using software frequently, the choice of software is also important. The software employed must be accessible and comprehensible for students. One participant underscored this point by saying, “Use software that students don’t have to pay attention to, so the focus is always on statistics.” Spreadsheet-based statistical packages such as that contained in Microsoft Excel were highly recommended, while more robust statistical packages were ill advised. One participant said, “Stay away from the powerful, esoteric packages—good interface design is never a bad thing!”

Along with familiarizing students with statistical software, using computer applications to illustrate statistical concepts was also important to experienced instructors. Using tools like applets that “bring concepts alive” such as scatterplots and correlation, spreadsheet simulations, and even games were among the suggested ways that computer technology adds value to statistics instruction.

3. Emphasize understanding rather than calculations. Focus on interpretation, not results. (Macro category: Focus on process and understanding)

As one instructor said, “show them that statistics is fundamentally not about math, it’s about concepts.” This idea was echoed by many in statements like, “Don’t teach math. Teach stats—it’s concepts more than numbers.” The point made by participants here is that students need to know from the first day of class that statistics is about logic and concepts, not math and formulas. Therefore, employing techniques such as beginning the course with a discussion of research questions and using regular language and logic before using notation to explain concepts were among the suggestions made by participants. As one participant indicated, “Use math derivations very sparingly, and only when they provide crucial understanding.” In other words, leave out the math except when it is essential. This is highlighted by the comment made by one instructor, “Always use ‘natural language’—e.g., stating hypotheses in words or as a question before presenting in symbols and then concluding in words.”

4. Take steps to acknowledge and manage anxiety of the students. (Macro category: Student-centric considerations)

As just suggested, deemphasizing math was certainly a common message among instructors. However, some math is typically necessary, and math deficiencies and fear are real among students. So, while experienced instructors emphasize that statistics is more about logic than about math, instructors suggested several things to ameliorate some of the math anxiety. For example,
offer a short math refresher for “brushing up” before the semester of statistics begins, give a brief math quiz at the beginning of the class to give students an idea of what kinds of math skills will be required for the course, provide a formula sheet for exams, and consider giving open-book exams.

5. Require group work both in and outside of class in very small groups.
(Macro category: Student-centric considerations)

Requiring group work for most aspects of a statistics course was another common theme among instructors participating in this study. Group work requires students to explain concepts to each other, which reinforces understanding rather than results. In addition, group work is another tool for managing student anxiety about statistics. One instructor even said, “Encourage working in pairs on everything except tests.” Instructors suggested techniques such as posing a question to the class and requiring students to think through their response with a neighbor before answering the question and using small groups, each equipped with a flip chart and an assignment to create, for example, a histogram by hand. However, one distinct was evident in comments regarding group work. While most instructors emphasized the value of group work, many instructors also indicated that groups are most effective when they are no larger than two students. As one instructor indicated, “I find this better than small groups in terms of everyone learning.”

6. Give students plenty of opportunities to practice.
(Macro category: Student-centric considerations)

For many, anxiety is the product of uncertainty. Giving students plenty of examples and practice opportunities will help reduce anxiety and reinforce what the instructor wants them to learn. Among the techniques suggested by instructors for providing practice are handing out past exams; developing and distributing additional sets of practice problems; letting students choose among a set of possible homework questions; giving out answers to practice problems; arranging for an online discussion group for “rapid feedback on questions”; and holding small-group problem-solving sessions.

7. Exude passion, excitement, and even drama for the subject.
(Macro category: Student-centric considerations)

In any class, students thrive on the passion communicated from the instructor. Statistics is no exception. One instructor suggested that when covering topics such as the central limit theorem, drama is not only appropriate but advised. In the same vein, instructors also can “show [students] that understanding a problem is cool.”

The four challenges inherent in teaching statistics to students enrolled in practitioner-oriented master’s degree programs are not necessarily distinct, but rather intertwined. As depicted in Figure 2, the clusters of ideas generated for addressing each of the four challenges are linked to the four macro categories identified: use of relevant real-life applications, use of technology, focus on process
and understanding, and student-centric considerations (bold in Figure 2). Each of the four macro categories are linked to several clusters of ideas, to the seven pieces of advice just discussed, and to more than one of the challenges associated with teaching statistics.

Figure 2 also shows how each of the macro categories of clusters of ideas addresses more than one of the four challenges. So, for example, clusters of ideas generated by participants related to the macro category use of relevant real-life applications were generated as ways to address challenge 1, challenge 2, challenge 3, and challenge 4. In the same spirit, clusters of ideas in the focus on process and understanding macro category were generated as ways to address challenge 1, challenge 3, and challenge 4. This suggests two things. First, that certain tools and techniques may be important for addressing more than one challenge. Second, if certain tools and techniques may be important for addressing more than one challenge, it is also likely that these four challenges are not independent, but rather intertwined. Therefore, identifying a specific challenge in teaching statistics to students enrolled in practitioner-oriented master’s degree programs and the particular tools that will address that specific challenge may not be the most effective approach. Rather, identifying the system of challenges and how the challenges are related to one another may be a useful way to think about overcoming these challenges and, consequently, improving statistical skills of students.

Implications for a Model of Research Production and Research Use

This study focused on one piece of the right-hand side of our original model of research production and research use (see Figure 1), specifically, practitioner quantitative (statistical) skills to understand and use research findings. Because the findings from the data collection exercise indicated that the four primary challenges associated with teaching statistics in practitioner-oriented master’s degree programs are intertwined rather than independent of one another, we integrated the theoretical foundations of the study and literature with the preliminary interviews to expand this portion of the model. By examining the collection of insights from these sources, we have expanded the segment of our model that focuses on practitioner quantitative skills. Figure 3 depicts this expanded model.

The revised version of this model describes how the four challenges associated with teaching statistics to students enrolled in practitioner-oriented master’s degree programs (in italics in Figure 3) are part of a larger system that links the production of research to the consumption of research. While each of these challenges influence practitioner quantitative skills to understand and use research findings either directly or indirectly, this model underscores the hypothesized links between the challenges as well. For example, the quantitative underpreparedness of students increases student anxiety about statistics; decreases
Figure 3. Expanded Model of Research Production and Research Use

- **Techniques in Teaching Statistics**

- **Other antecedents of quantity, quality and relevance of research production**
  - Researcher quantitative (statistical) skills to produce quality and relevant research

- **Other antecedents of extent and adequacy of research use**
  - Quantity, quality, and relevance of research production
  - Success of policy implementation and increased perceived value and worth of statistics use

- **Practitioner quantitative (statistical) skills to understand and use research findings**
  - Extent and adequacy of research use
  - Availability and Use of Tools effective for learning
  - Desire to memorize, not understand

- **Anxiety about statistics**
  - Motivation, participation, and engagement

- **Quantitative under-preparedness**

- **Other antecedents of extent and adequacy of research use**
  - Motivation, participation, and engagement
  - Availability and Use of Tools effective for learning

- **Success of policy implementation and increased perceived value and worth of statistics use**

- **Desire to memorize, not understand**

- **Availability and Use of Tools effective for learning**

- **Motivation, participation, and engagement**

- **Anxiety about statistics**
student motivation, participation, and engagement; increases students’ desire to memorize, not understand; and helps decrease practitioner quantitative skills to understand and use research findings. As anxiety about statistics increases, student motivation, participation, and engagement decreases. Furthermore, as student motivation, participation, and engagement decreases, anxiety about statistics increases even further.

Among the important hypothesized relationships in this model are several feedback mechanisms, indicated by R1, R2, R3, and R4 and identified with bold arrows in Figure 3. As discussed in the introductory section of this paper, the first feedback mechanism, the *production-consumption* loop (R1), shows the positive feedback relationship between the production of research and the consumption of research. As the quantity, quality, and relevance of research production increases, ceteris paribus, the extent and adequacy of research use will also increase. In addition, as research is used more by practitioners, the quantity and quality of research that is relevant to practitioners being produced will also increase. Thus a positive reinforcing feedback mechanism, which exists between the production and consumption of research, is created.

Building on the positive reinforcing relationship between the production of research and the consumption of research, the *improvement-by-success* loop (R2) hypothesizes that as practitioner quantitative skills to understand and use research findings increase, so will the extent and adequacy of research use. As the extent and adequacy of research use increases, the success of policy implementation increases; and the perceived value and worth of statistics will also increase. When the success of policy implementation and perceived value and worth of statistics use increases, this will only further increase practitioner quantitative skills, thus creating a positive reinforcing mechanism between practitioner quantitative skills, use of research, and success of research-based policy implementation.

In the *tools-influence-attitude* loop (R3), two of the challenges inherent in teaching statistics, designing tools effective for learning and student desire to memorize, not understand, are salient. In this feedback mechanism we capture the idea that with increased availability and use of tools effective for learning, the students’ desire to memorize, not understand decreases, leading to higher levels of quantitative skills. With increased quantitative skills, higher levels of use of research will be achieved, leading to additional success of policy implementation that, in turn, will increase the availability and use of tools that are effective for learning (e.g., successful real-life case studies to be used in the classroom). Therefore, we can see how these two challenges are part of a complex causal connection between the success of policy implementation and perceived value of statistics and the level of practitioner quantitative skills achieved. Moreover, these challenges, determine, over time, how success is achieved and how success can be used to further develop the potential for future success in the form of practitioner quantitative skills.
Lastly, the anxiety-and-motivation loop (R4) captures the interaction of skill development, anxiety, and motivation of students. In this loop, we see that as quantitative skills increase, the level of anxiety about statistics decreases, bringing student motivation, participation, and engagement up. As motivation grows, further increased levels of practitioner quantitative skills are achieved. The reinforcing process just depicted can become either an engine of success or a vicious cycle of failure. To deactivate the possibility of being locked into a downward spiral of high anxiety and low motivation, dealing with the quantitative underpreparedness of students, making use of relevant real-life applications, and developing student-centric considerations may be useful.

**DISCUSSION**

Returning to the initial motivation of this study, we want to work toward shrinking the research-practice gap by examining factors that influence the consumption of research by practitioners—in particular, the ability to comprehend and employ statistical techniques.

If closing the research practice gap is important, then reflecting on and improving statistics instruction seems desirable. The development of practitioner statistics skills in the classroom is constrained by anxiety about statistics, quantitative underpreparedness, student desire to memorize rather than understand, challenges in developing tools that are effective for learning, and general lack of student motivation, participation, and engagement. By addressing these challenges with teaching techniques such as making interpretation rather than results a priority, using relevant real-life examples, requiring data collection exercises, employing computer applications, and so on, we may increase practitioner statistical skills. Increased practitioner statistical skills will, in turn, lead to increased research use. Increased research use then will lead to an increase in relevant, high-quality research production and thus shrink the research-practice gap.

Viewing the challenges associated with teaching statistics from a systems perspective is valuable. Understanding how one challenge may influence other challenges is useful when considering tools and techniques for addressing such challenges. So, for example, coming up with ways to address quantitative underpreparedness before taking a statistics course may serve to reduce anxiety; increase motivation, participation, and engagement; and ultimately result in an increase in practitioner quantitative skills. In addition, designing tools effective for learning will increase practitioner quantitative skills. Such tools will also decrease student desire to memorize, not understand, and this attitude in turn will increase practitioner quantitative skills.

A broader point that can be derived from this thinking is that to increase the likelihood of successfully addressing the research-practice gap, the use of a systems approach seems warranted. Part of the model of research production and
research use presented here underscores the relationships between the various challenges in teaching statistics and how particular tools and techniques may influence practitioner quantitative skills and ultimately the research-practice gap.

**Contributions, Limitations, and Directions**

This project contributes to both research and practice in two primary ways. First, our study employs a systematic method to identify recommended teaching practices. To our knowledge, an electronic Delphi technique has not been used before for identifying areas of agreement among statistics instructors. In this study, we recognize the importance of experience and move understanding forward in this area by building on the work of Desai (2008), Mandell (2008), and Aguado (2009) by systematically collecting opinions from experienced statistics instructors to develop aggregate views.

Second, the categories, ideas, and subsequent model provide aspects of teaching statistics that could and should be tested empirically in the classroom setting. Testing portions of this model in the classroom could provide a way to evaluate the effectiveness of different techniques with the student component included.

Like all studies, the one presented here has limitations. First, the number of participants was lower than the target number. Second, dialogue among the participants was limited by the nature of the online discussion tool used. The Web-wide participation tool allowed the moderators to conduct a group discussion with participants in a variety of time zones, thus eliminating the cost of holding focus groups across the United States. However, the pseudo-group discussion was not in real time and thus limited in-depth conversation among participants.

Emerging from this study are several directions for future research. First, this study examined the opinions of “experienced” faculty. Comparing the results found here with the practices used by “new” faculty may prove insightful. Second, examining how such ideas are put into practice through classroom observation and interviews may provide greater depth to this study with the inclusion of a student perspective. Third, while a Web-based discussion tool was used for this project, it may be beneficial to discuss results in person in small groups within university departments or at academic conferences. Finally, these types of studies address the teaching of statistics to practitioners. Developing additional studies to determine how practitioners actually use statistics and to identify the needs of practitioners would be valuable.

Practices that work well for one may not necessarily work well for another. Effectiveness of the suggestions provided here are undoubtedly relative to the course, the instructor, the program, and the student, among many factors. However, this project has systematically identified ideas that might serve as starting points for new faculty and that might be worth revisiting for experienced faculty. We hope that using such techniques to train future practitioners will help practitioners become better consumers of research and make better use
of research in their decision-making processes, resulting in improved policy outcomes. The results of this research imply that improving the way in which practitioners use research is not a single-actor problem or a matter of “changing the other side” (Shapiro et al., 2007, p. 261); the solution might very well involve the interaction of researchers, educators, and practitioners. This research recognizes that the tension between the producers and the consumers of research should be used to identify ways to coproduce actionable knowledge of high quality and relevance for practice, as suggested by Van de Ven and Johnson (2006), and to train current and future consumers of research. Ultimately, as Shapiro et al. (2007) suggest, if all the actors participate in the process, this process will strengthen the relationship between research and practice.

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FOOTNOTES
1 This manuscript has been created by UChicago Argonne, LLC, Operator of Argonne National Laboratory ("Argonne"). Argonne, a U.S. Department of Energy Office of Science laboratory, is operated under Contract No. DE-AC02-06CH11357. The U.S. Government retains for itself, and others acting on its behalf, a paid-up, nonexclusive, irrevocable worldwide license in said article to reproduce, prepare derivative works, distribute copies to the public, and perform publicly and display publicly, by or on behalf of the Government.

2 See Bisgaard (1991) and Sowey (1995) for examples of experiential learning with statistics.

3 The final version of the questions was developed after pre-testing and pilot testing with several colleagues and statistics instructors.

4 Details on the computations for the prioritization step are available upon request.

REFERENCES


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**APPENDIX A**

**Data Collection Questions**

1. If you were offering advice on the best way to teach statistics to students in practitioner-oriented master’s degree programs, what activities would you say are essential for addressing the challenges of designing and/or selecting tools effective for learning? (For example, software, textbooks, examples, in-class exercises, projects, course content and level of detail, etc.)

2. If you were offering advice on the best way to teach statistics to students in practitioner-oriented master’s degree programs, what activities would you say are essential for addressing the quantitative underpreparedness and math anxiety of students?

3. If you were offering advice on the best way to teach statistics to students in practitioner-oriented master’s degree programs, what activities would you say are essential for addressing students’ tendency to want to memorize instead of understand?

4. If you were offering advice on the best way to teach statistics to students in practitioner-oriented master’s degree programs, what activities would you say are essential for addressing the low levels of motivation, participation, and engagement of students.