TEACHING THE CONCEPT OF THE SAMPLING DISTRIBUTION OF THE MEAN

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The authors use proven cognitive and learning principles and recent developments in the field of educational psychology to teach the concept of the sampling distribution of the mean, which is arguably one of the most central concepts in inferential statistics. The proposed pedagogical approach relies on cognitive load, contiguity, and experiential learning theories and on the integration of new knowledge within previously formed knowledge structures. Thus, the proposed approach stimulates both visual and auditory learning, engages students in the process of learning through problem solving, and presents information so that it builds on existing knowledge. Results of an experiment including introductory statistics undergraduate students indicate that students exposed to the proposed theory-based pedagogical approach enhanced their learning by approximately 60%.

Keywords: *teaching statistics; sampling distribution of the mean; inferential statistics; statistics pedagogy; statistical methods; research methods education; statistics education*

Authors' Note: A previous version of this article was presented at the 2006 Academy of Management meetings in Atlanta, Georgia. We thank Kenneth G. Brown (University of Iowa), Peter G. Bryant (University of Colorado at Denver and Health Sciences Center), Kurt Kraiger (Colorado State University), Charles A. Pierce (University of Memphis), and Raymond F. Zammuto (University of Melbourne) for helpful comments on previous drafts. We also thank Journal of Management Education (JME) Co-Editor Susan J. Herman and three JME anonymous reviewers for their constructive and detailed feedback during the review process. This research was supported in part by a Summer Grant from the Business School (University of Colorado at Denver and Health Sciences Center) to Herman Aguinis. Please address correspondence to Herman Aguinis, the Business School, University of Colorado at Denver and Health Sciences Center, Campus Box 165, P.O. Box 173364, Denver, CO 80217-3364; phone: (303) 556-2512; fax: (303) 556-5899; e-mail: Herman.Aguinis@cudenver.edu. Internet: http://www.cudenver.edu/~haguinis.

JOURNAL OF MANAGEMENT EDUCATION, Vol. 31 No. 4, August 2007 467-483
DOI: 10.1177/1052562906290211

There is Nothing So Practical as a Good Theory
—Kurt Lewin (1951, p. 169)

For many years, the Association to Advance Collegiate Schools of Business (AACSB) accreditation standards have included a Common Body of Knowledge (CBK) that was required of all business majors (AACSB, 2001). For example, the 2001 AACSB standards note that "the curriculum should include foundation knowledge for business in the following areas: accounting, behavioral science, economics, and, mathematics and *statistics* [emphasis added]" (standard C.1.2.b). Similarly, the most recent version of the standards, revised in January 2006, note that

> the curriculum management process will result in undergraduate and master's level general management degree programs that will include learning experiences in such management-specific knowledge and skills areas as: . . . *Statistical data analysis* [emphasis added] and management science as they support decision-making processes throughout an organization. (AACSB, 2006, pp. 15-16)

Likely, the perceived importance of teaching quantitative data analysis techniques (Aiken et al., 1990), combined with AACSB accreditation standards regarding the need to include such a course as part of the core curriculum, has led most undergraduate business programs to include a course in introductory statistics. In fact, we are not aware of any undergraduate business program that does not require an introductory data analysis or statistics course as part of the core curriculum.

The concept of sampling distributions is arguably the single most important concept in inferential statistics (Hopkins, Hopkins, & Glass, 1996). Sampling distributions are the gateway to understanding hypothesis testing regarding correlation coefficients, regression coefficients, proportions, means, and numerous other statistics (Aguinis, 2001, 2004; Aguinis, Beaty, Boik, & Pierce, 2005; Aguinis & Pierce, 1998; Aguinis & Whitehead, 1997). In most introductory statistics courses, students learn about raw scores, measures of central tendency, measures of variability, and frequency distributions of raw scores. Soon hereafter, students make a qualitative leap to sampling distributions, which are often treated as an entirely new concept, separate from all they have previously learned. Because of its importance as a key statistical concept, the concept of sampling distributions plays a prominent role in most business and management statistics textbooks (e.g., Anderson, Sweeney, & Williams, 2003; Lind, Marchal, & Wathen, 2001; Taylor, 2001).

The sampling distribution of the mean is typically the first theoretical sampling distribution taught to introductory statistics students not only in business schools but also in psychology and other social and behavioral sciences (e.g., Freund, 2004; Gravetter & Wallnau, 2004; Heiman, 2003). A good understanding of the sampling distribution of sample means is necessary because it lays the foundation for working with all subsequent sampling distributions and sets the stage for learning inferential statistics. Accordingly, it is of paramount importance that students understand the concept of the distribution of sample means when it is first introduced.

The concept of sampling distributions can be as abstruse and anxiety provoking for students to learn as it is for instructors to teach. When it comes to sampling distributions, even the most enthusiastic instructor may revert to the one-way lecture-driven method in which formulae are presented and confused student questions are answered with the statistician's equivalent of "trust me." Textbook coverage is often no more sensitive to the conceptual difficulty of sampling distributions. The importance of the concept is stressed but is frequently followed by a few short pages of abstract theorizing and a quick progression to applications.

Criticism has been raised regarding how social and behavioral scientists teach introductory statistics courses (e.g., Hogg, 1991; Snee, 1993; Watts, 1991), and numerous calls have been made to improve the process. These criticisms point to an underutilization of cognitive and learning principles that could improve student learning. Among the many suggestions are that (a) instructors express enthusiasm and excitement about statistics (Hogg, 1991), (b) student participation be increased (Magel, 1996), and (c) meaningful data sets and graphics be used (Bradstreet, 1996).

In short, a challenge faced by instructors teaching introductory statistics to business and other social science majors is how to improve learning, including learning the key concept of the sampling distribution of the mean, by adopting a theory-based approach to teaching in which instructors use proven theories to improve learning. Although the suggestions offered by Hogg (1991), Magel (1996), and Bradstreet (1996) are useful, how can enthusiasm and excitement be expressed for sampling distributions? How can students participate in the introduction of a purely theoretical concept? Finally, how can instructors incorporate meaningful data and graphics as they teach such an abstract topic? To answer these questions, this article describes a theory-based approach to teaching the concept of the sampling distribution of the mean. We refer to our pedagogical approach as a "theory-based approach" because it relies on proven theories and principles about pedagogy and instruction as well as recent developments in the field of educational psychology. In other words, our goal is to propose a pedagogical technique, rooted in theory-based principles, for addressing the challenging and unavoidable task of teaching the concept of the sampling distribution of the mean.

Although the basic principles involved in our approach are not new, we are not aware of previous efforts to use these principles in an integrated manner and in the specific context of teaching the sampling distribution of the mean. The synthesis of techniques we propose seems to be novel, based on the fact that none of the textbooks we reviewed have proposed it. In addition, we conducted an extensive experimental study to document the effectiveness of the proposed approach. Although we do not provide details regarding research design, measurement, and results in this article, we make this information regarding the experimental study available to interested readers upon request (please contact the first author to obtain this information).

The theory-based approach to teaching was developed on the basis of proven cognitive and learning principles and recent developments in the field of educational psychology. First, a consistent finding in the psychological literature is that visually presented material is remembered more easily than material presented auditorially (e.g., Kirkpatrick, 1894; Shepard, 1967). Likely, this finding is produced by humans' inability to process large amounts of auditory information, whereas the presentation of information visually tends to reduce cognitive load, particularly in learning complex information and tasks (cf., Paas & Van Merriënboer, 1994). In addition, material presented in both images and words is more accurately recalled later than information presented using either images or words alone (Galotti, 1994). The finding of superior learning when words and pictures are presented contiguously in time and space has been labeled the contiguity principle (Moreno & Mayer, 1999). In short, because of the superiority of visual over auditory material and the contiguity principle, a theory-based approach to teaching the concept of the sampling distribution of the mean could incorporate graphs and figures designed to help students visualize the basic concept of sampling distributions.

Second, it is also well known that active student interaction in problem-solving processes facilitates learning (Cross, 1986). This is a basic principle of the various experiential learning approaches available (Dewey, 1958; Kolb, 1984; Piaget, 1970). Experiential learning does not ignore the cognitive processes of acquiring, manipulating, and recalling abstract information. Rather, it integrates these more basic cognitive and behavioral principles by presenting students with situations in which learning takes place by solving problems that are relevant to students' own experiences (Kolb, 1984). Consequently, a theory-based approach to teaching the concept of the sampling distribution of the mean could adopt a participatory and problem-solving approach to classroom learning.

Third, knowledge acquisition is more effective when new information is integrated and compiled within previously acquired knowledge structures (Gagné & White, 1978). Accordingly, a theory-based approach to teaching the concept of the sampling distribution of the mean could build on existing knowledge that students have acquired in the preliminary phase of the introductory statistics class, thereby making the introduction of sampling distributions not seem as far removed from previously learned material.

In sum, we propose the use of a theory-based approach to teaching in which we stimulate both visual and auditory learning, engage students in the process of learning, and present information in a manner that builds on existing knowledge of probability and frequency distributions. As a consequence, we hypothesize that learning of the concept of the sampling distribution of the mean will be enhanced as compared to more traditional teaching methods presented in most introductory business and social and behavioral science statistics textbooks.

Description of the Theory-Based Pedagogical Approach

The proposed theory-based approach to teaching the concept of the distribution of sample means uses the aforementioned pedagogical and learning principles to facilitate learning. The method includes eight steps, each one based on one or more of the principles described above. The steps are described below.

INTRODUCTION OF PROBLEM

Students are presented with the problem of determining if their instructor is older than the average age of the students in the class he or she is teaching. This problem was chosen because it (a) uses a salient and realistic data type (i.e., age), (b) uses a simple problem that builds on students' knowledge of probability testing using z-scores (i.e., instructor's age X vs. the mean age $\bar{X}$ of the students in a particular class), and (c) requires student participation to solve the problem.

PROBLEM SOLVING

Students are asked to solve the problem presented, and suggested solutions are tallied on the blackboard. Students are allowed to continue generating ideas until they have suggested at least the following: (a) obtain the instructor's age, (b) obtain each individual student's age, (c) compute the class mean age, (d) determine the standard deviation for the student age scores, and (e) use an appropriate statistic to determine the difference between the instructor's age and the class mean (i.e., z test).

REVIEW OF SOLUTION

Using a graph of a frequency distribution shown in Figure 1, students are shown how the age of each student can be compiled into a distribution with

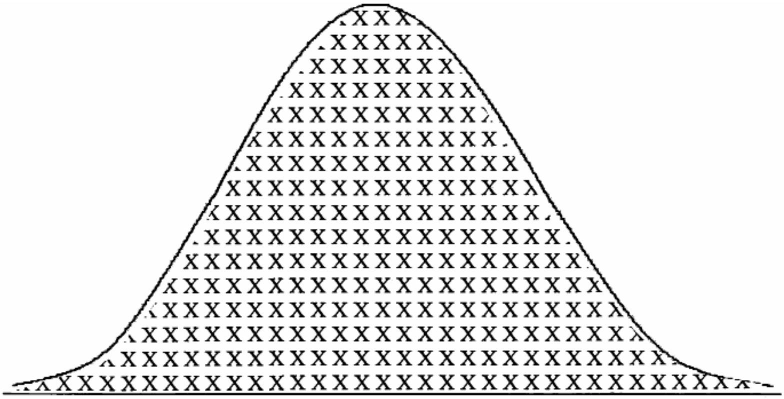

Figure 1: Frequency Distribution of Raw Scores

a mean and a standard deviation. Then, the instructor reviews how the *z* test attempts to find the probability of obtaining a specific single age (i.e., the instructor's age) from the frequency distribution of the students' age scores.

INTRODUCTION OF NEW PROBLEM

Students are then told to determine if a given sample of instructors is older than all students enrolled in statistics courses in the United States (i.e., the population). In addition, they are told that there are no existing normative data for students in statistics courses (i.e., no mean ages). This problem is selected because it builds from the previous problem and helps bridge the gap between two concepts: (a) frequency distributions, which students used to determine if the instructor was older than the students in the course, and (b) sampling distributions, which they need to use to compare the age of the sample of instructors to the age of the population of students.

PROBLEM SOLVING

Again, students are asked how to solve the new problem. Suggestions about solving the problem are tallied on the blackboard. Students are allowed to continue (and are assisted) until they offer at least the following suggestions: (a) find the ages of all students in statistics courses in the United States and compute the mean, (b) obtain the mean age of the given sample of instructors, and (c) perform an appropriate test to determine statistical significance.

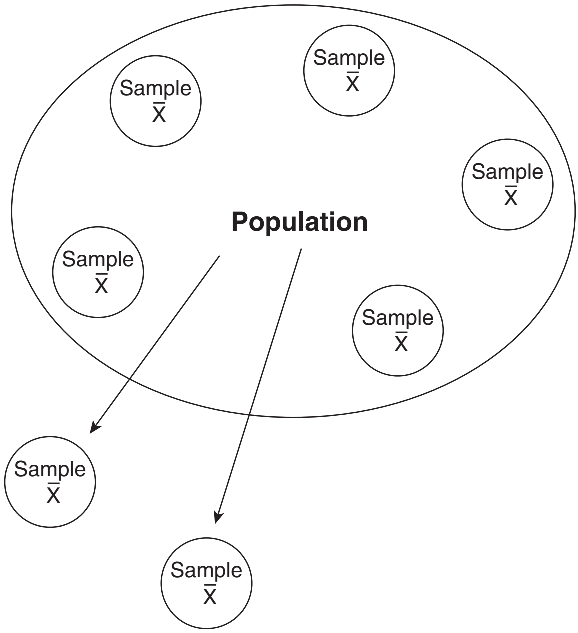

Figure 2: Graphic Illustration of the Process of Sampling Means From a Population

SAMPLING FROM THE POPULATION

Students are then reminded that, in the first problem, a solution was found by visually estimating where a single raw score X fitted in a distribution of other raw scores (i.e., Xs). Then, the following question is posed: “Against what, then, do you compare our mean age $\bar{X}$ from the sample of instructors?” Students offer suggestions until they determine that the sample of instructor ages must be compared against other sample means (i.e., $\bar{X}$s). A graph shown in Figure 2 is used to show how samples are drawn from the population to construct a new “frequency distribution” of sample means.

DISTRIBUTION OF SAMPLE MEANS

A graph identical to the previously used frequency distribution (i.e., Figure 1) is introduced to demonstrate what a distribution of sample means may look like, with $\bar{X}$s rather than Xs under the curve (see Figure 3). Students are shown how the mean age of our sampled instructors could then

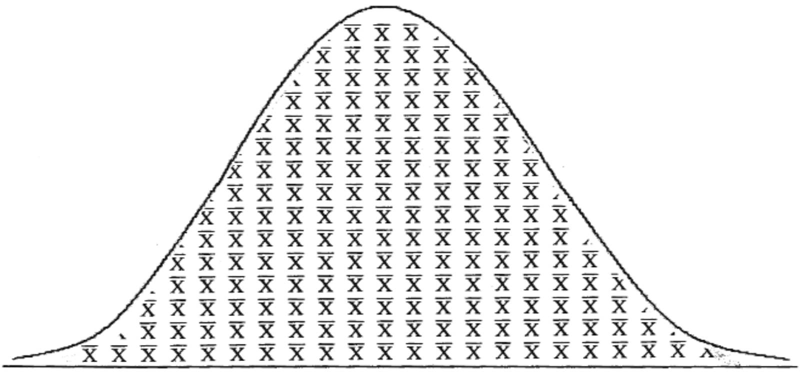

Figure 3: Sampling Distribution of Means

be compared to the distribution of sample means taken from students. The difficulty of actually sampling every section of statistics at every university is discussed, and students are asked to offer reasons why this type of sampling of the population may be problematic. Students are encouraged until they suggest that this type of sampling would be (a) expensive, (b) difficult logistically, and (c) all possible samples may not be obtained. Subsequently, the theoretical construction of the distribution of sample means is discussed, as is the Central Limit Theorem.

COMPARISON AND CONCLUSION

Using Table 1, similarities and differences between frequency distributions and sampling distributions are shown and discussed. Finally, the role of the distribution of sample means in inferential statistics is highlighted. Attention is given to the similarities between the *z* test and *t* test and the difference between individual scores (i.e., Xs) and group scores (i.e., $\bar{X}$s).

Next, we provide a brief overview of an experiment designed to assess the effectiveness of the theory-based approach to teaching.

Assessing the Method's Effectiveness

We implemented a pre-post with comparison group design (Haccoun & Hamtiaux, 1994) in which 30 undergraduate students enrolled in an introductory statistics course were given a pretest to assess their conceptual understanding of (a) general statistics concepts previously learned in the

TABLE 1
Table Comparing Characteristics of Frequency and Sampling Distributions

Frequency Distribution	*Sampling Distribution*
"X"	$\bar{X}$
Individual score	Group / sample score
Standard deviation	Standard error
Average	Expected value
Used to determine probability of *individual* score	Used to determine probability of *group* or *sample* (*hypothesis testing)*
Based on actual data (*empirically derived)*	Based on theoretical data and Central Limit Theorem (*theoretically derived)*

class (i.e., "irrelevant questions") and (b) concepts relating to the distribution of the sample mean (i.e., "relevant questions"). These questions are included in Appendix A; those with odd numbers are relevant items, and those with even numbers are irrelevant items.

All students were then exposed to a traditional lecture, as presented in most introductory statistics textbooks, on the distribution of sample means (see Appendix B). Following the introductory lecture, a control group was given another identical traditional lecture on the distribution of sample means. An experimental group was exposed to the theory-based teaching approach described above. Subsequently, each group was given a follow-up assessment (i.e., posttest) including the same irrelevant and relevant questions used in the pretest. For ethical reasons, anticipating that the theory-based approach would be more effective at enhancing learning than the traditional method, all students were exposed to the proposed approach at the conclusion of the study.

Results based on a paired-samples *t* test suggested that, as expected, there was no change in performance between pre- and postintervention scores for the mean of the 10 irrelevant items for the control group (t = 2.25[9], $p > .05$) or the experimental group (t = 1.54[9], $p > .05$). Most important, also as expected, students in the experimental group experienced a significant performance improvement as assessed by the mean score across the 10 relevant questions (t = 9.35[9], $p < .001$). In addition, follow-up paired-samples *t* tests indicated that improvement occurred on each of the 10 relevant items. Moreover, the success rate, as measured by the binomial effect size statistic (i.e., percentage of students answering an item correctly; Rosenthal & Rubin, 1982), increased from about 20% to about 80%, yielding an improvement of about 60% in correct responses. These results indicate that the theory-based approach did indeed help students gain a deeper conceptual understanding of the concept of the sampling distribution of the mean.

Discussion

The goal of this article was to describe a theory-based approach to teaching the concept of the sampling distribution of the mean. We focused on the specific case of the concept of sampling distributions because it plays such a central role in statistics courses. It is unlikely that students will have a good understanding of hypothesis testing and inferential statistics in general without a good conceptual understanding of sampling distributions. We use the phrase "theory-based" because the proposed pedagogical approach relies on proven cognitive and learning theories and principles about pedagogy and instruction as well as recent developments in the field of educational psychology. We also provided a brief description of an experimental study aimed at evaluating the effectiveness of the proposed pedagogical approach.

Our theory-based approach to teaching was designed following well-established theories and principles in educational psychology and related fields. So, the basic principles underlying our pedagogical approach are not new. Our theory-based approach relies on cognitive load, contiguity, and experiential learning theories and on the integration of new knowledge within previously formed knowledge structures. The theory-based approach allows students to form a logical conceptualization of the sampling distribution of the mean and learn to rely less on a mechanical, rote memorization of formulae. Consequently, in our experience using this pedagogical approach for several years, students seem to feel less intimidated by what was formerly a daunting and abstract statistical theory. Using this approach, students learn that the gateway to inferential statistics, the sampling distribution, is no more than a theoretically constructed "frequency distribution" of means (or frequency ratios, or correlation coefficients, and so on), and that hypothesis testing using the sampling distribution is similar to probability testing with individual raw scores and frequency distributions.

We speculate that the general principles that we used in designing a pedagogical approach useful for teaching the concept of the sampling distribution of the mean could be used for teaching other similarly difficult concepts in statistics and other management courses, such as random sampling, chance, and correlated and uncorrelated data, among others. For example, consider the case of the concept of *random sampling*. Although this concept is important, and often seems intuitive, in our experience, many students misunderstand the concept. For example, students occasionally object to a study because they "know Jane" for whom "X" was not the case, or they doubt the results of a survey because "no one asked me."

When students truly understand that accounting for individual variance is one purpose of the random sample, they can begin to accept that research results can be characterized as reflecting a sample or population in general but do not necessarily represent any one person in particular.

Our proposed pedagogical approach for teaching the concept of the sampling distribution of the mean can be adapted to teach the concept of random sampling. In this exercise, students would apply earlier lessons on random sampling in a practical manner. For example, the instructor can assign the task of estimating the number of words in the course's textbook. This number represents a good example of a population because the exact parameter is unknown, but it can be estimated through random sampling.

First, an instructor would assign small groups of students "random" pages in the textbook. The students would carefully count each word on their assigned page (this may also provide a good introduction to operational definitions: what counts as a "word"?). The instructor would intentionally assign one group a text-heavy page (e.g., a references page) and another group a text-light page (e.g., chapter heading; pages with large graphics or pictures). The other groups would be assigned text pages that are more representative of the book. When the students have completed the task, they would inform the instructor of the number of words on their assigned page. The instructor can then demonstrate the differences between the text-heavy sample and the text-light sample by multiplying the number of words on each page by the total number of pages in the book. For example, the text-heavy page might have 712 words. If the textbook has 628 pages, the instructor can claim that one group estimates the textbook has 447,136 words. If the text-light page has 30 words, the instructor can note that the second group estimates 18,840 words are in the text. Incorporating the remaining more representative sample pages would give students an idea of the importance of random sampling and help them recognize that although individual pages may vary, the sample of sufficient size is typically a fair estimation of the population. Graphing the results under a normal curve will help students see that the text-heavy page is at one end of the distribution, the text-light page is at the other, and the other pages fill in the middle of the distribution.

In short, one could teach the concept of random sampling using the principles outlined in this article: use visual materials (i.e., graph the number of words per page, including extreme values), apply the contiguity principle (i.e., actively plot a graph while the concept of random sampling is introduced), use experiential learning and a problem-solving approach to learning (i.e., number of words in a book, based on randomly sampling pages), and promote knowledge acquisition based on previously acquired knowledge structures (i.e., build the random sampling exercise on previous sampling lectures).

In addition to describing the theory-based approach, this article provided a brief description of an experiment whose results indicated that the approach enhances learning. Results showed that students exposed to the theory-based approach had a greater improvement in their understanding of the concept of the sampling distribution of the mean compared with students exposed to a traditional method. Moreover, students exposed to the theory-based approach improved their performance by 60%. Detailed information regarding the methods, measures, and results obtained from this evaluation study can be obtained by contacting the first author.

LIMITATIONS AND FUTURE DIRECTIONS

We acknowledge three potential limitations of our article as well as two avenues for future research. In terms of limitations, as correctly noted by a *Journal of Management Education* (*JME*) anonymous reviewer, our evaluation study was limited to measures of learning and did not include measures concerning student affective reactions. A meta-analysis summarizing results of 34 independent studies ascertained that the average correlation between reactions to training and learning is only $\bar{r} = .07$ (Alliger, Tannenbaum, Bennett, Traver, & Shotland, 1997). In other words, the relationship between reactions and learning is practically nonexistent because knowledge of reactions explains only about 0.5% of variance in learning scores (i.e., $\bar{r}^2 = .07 \times .07 = .0049$). Thus, although our evaluation study provided convincing evidence regarding student learning, we do not have quantitative information regarding students' reactions. These reactions are most useful and provide most information when they are measured using utility judgments such as "Was the material of practical value?" or "To what extent was the material instrumental in allowing you to do better in this course?" Reactions conceptualized as utility judgments yield useful information because they are somewhat correlated with future performance (i.e., $\bar{r} = .18$). In fact, Alliger et al. (1997) found that utility judgments are better predictors of future performance than are measures of learning (such as the ones we used in our evaluation study). In sum, although liking does not equate to learning or performing, one avenue for future research is to collect measures of students' *utility reactions* because they are more strongly related to future performance than measures of student learning.

A second limitation of our article is that, as noted by another *JME* anonymous reviewer, some instructors teaching introductory statistics courses may use practical examples taken from textbooks, may use visual materials such as figures and tables, and may attempt to engage students in the learning process. We acknowledge that some instructors, particularly seasoned ones, may use one or more of the principles underlying our proposed approach including using visual materials, applying the contiguity principle, using experiential learning and a problem-solving approach to learning, and promoting knowledge acquisition based on previously acquired knowledge structures. However, as noted in the introduction, although the basic principles involved in our approach are not new, we are not aware of previous efforts that have used these principles in an integrated manner and in the specific context of teaching the sampling distribution of the mean. The synthesis of techniques we proposed also seems to be novel based on the fact that none of the textbooks we reviewed have proposed it.

A third potential limitation of our article is that, although we gathered convincing evidence regarding student learning of the concept of the sampling distribution of the mean, we can only speculate regarding the effectiveness of the proposed pedagogical approach to teach other concepts. Thus, a second avenue for future research is to extend the pedagogical approach we proposed for teaching the concept of the sampling distribution of the mean to teaching other concepts in statistics as well as other courses. Possible extensions include teaching the concepts of random sampling, chance, and correlated and uncorrelated data, among others. Of course, such extensions would benefit from conducting evaluation studies to assess the extent to which the pedagogical approach is effective.

CLOSING REMARKS

In closing, the implementation of a theory-based approach to teaching including visual presentation of materials, applying the contiguity principle, using experiential learning and a problem-solving approach to learning, and promoting knowledge acquisition based on previously acquired knowledge structures allowed students to gain a deeper conceptual understanding of one of the most basic, and perhaps important, concepts in inferential statistics. We hope the proposed pedagogical approach will make it to the pages of mainstream statistics textbooks and allow instructors to teach the challenging and central concept of the sampling distribution of the mean more effectively. We also look forward to assessing the effectiveness of integrating the various learning principles and theories we have synthesized in teaching the sampling distribution of the mean to teaching additional concepts in statistics as well as other management courses.

Appendix A
Questions Included in the Self-Assessment

1. A theoretical distribution of a particular statistic (such as $\bar{X}$) for an infinite number of random samples of a specified size is called what type of distribution?
2. Using letter grades (A, B, C, D, and F) to classify student performances on an exam is an example of a(n) _________________ scale of measurement.

3. The standard deviation of the sampling distribution of the mean is called what?
4. To determine the semi-interquartile range, you must know the _______ percentile and the __________ percentile.
5. A theoretical distribution of an infinite number of means from random samples of a specified size is called the sampling distribution of ____________?
6. If you receive a score exactly equal to the mean, your *z*-score will be __________.
7. Describe what happens to the distribution of sample means when you increase the size of each sample.
8. When measuring to the nearest minute, the value of X = 6 would have real limits of ________ and _________.
9. In words, explain the meaning of the standard error.
10. The percentile rank for the median in a distribution is ________________.
11. Frequency distributions differ from sampling distributions in two ways. What are they?
12. Your score is 105 on a test with a mean of 100 and a standard deviation of 10. Your *z*-score is _______________.
13. What is a sampling distribution? What is its role in inferential statistics?
14. The standard deviation is a measure of a distribution's ________________.
15. Under what circumstances is the distribution of sample means guaranteed to be normal?
16. When the mean is *lower* than the median, you have a _______________ skewed distribution.
17. Describe reasons why a sample distribution of the mean typically consists of "theoretical" data and not actual data.
18. Parameter is to __________________ as statistic is to ________________.
19. In sampling distributions, standard deviations are referred to as ________________.
20. In all cases, $X - \bar{X}$ is equal to __________________.

Appendix B
Description of Traditional Lecture on the Sampling Distribution of the Mean

The following lecture outline is based on chapter 7 of Gravetter and Wallnau (2004). Each numbered general topic is discussed in further detail than is outlined here.

1. Introduction
   - 1.1. Two samples taken from same population are likely to be different.
   - 1.2. A large set of samples from a population makes it possible to predict the characteristics of a sample with some accuracy.
   - 1.3. The ability to predict sample characteristics is based on the "distribution of sample means."
2. Definition
   - 2.1. The distribution of the sample means is the collection of sample means for all possible random samples of a particular size (*n*) that can be obtained from a population.

3. Differences
    3.1. Distribution of sample means is different from previously encountered distributions. Before, we have looked at distributions of scores; now the values in the distribution are not scores but statistics.
4. Example
    4.1. We have a population of four scores (e.g., 2, 4, 6, and 8). We then sample this population for all possible samples of $n = 2$. We discover that we could get 16 different samples. If we compute the mean for each of the 16 samples, we have a distribution of sample means. We could then make some predictions of what we might expect from another (theoretical) sample of $n = 2$.
5. Central Limit Theorem
    5.1. Most constructions of the distribution of the sample means are not as simple as the above example.
    5.2. In most cases, it would not be possible to sample every possible combination of scores from an entire population.
    5.3. Therefore, it is necessary to develop general characteristics of a distribution of sample means that can be universally applied.
    5.4. Central Limit Theorem describes the distribution of sample means for any population. It tends to be a normal distribution if either one of the following conditions is met:
        5.4.1. The population from which the samples are selected is a normal distribution.
        5.4.2. The number of scores (n) in each sample is large, around 30 or more.
6. The Mean of the Distribution of Sample Means
    6.1. The average of the samples obtained for the distribution of the sample means is called the expected value of .
    6.2. In our example of the 16 samples of $n = 2$, we could obtain an average of the averages (e.g., $\bar{X} = 4.9$). If we were to guess the value of a new sample mean, and given no further information about the sample, we would expect to get $\bar{X} = 4.9$.
7. The Standard Error of $\bar{X}$.
    7.1. From the Central Limit Theorem we learned the shape and central tendency of the distribution of the sample means. Now we need a measure of variability.
    7.2. The standard error of $\bar{X}$ is similar to the standard deviation of a frequency distribution: It tells us the typical deviation from the expected value of $\bar{X}$.
8. Probability and the Distribution of Sample Means
    8.1. The utility of the distribution of sample means is to find the probability associated with any specific sample.
    8.2. Example
        8.2.1. Population of scores on the Graduate Record Examination (GRE) forms in a normal distribution is $\mu = 500$ and $\sigma = 100$.
        8.2.2. What is the probability that a sample of $n = 25$ would have an $\bar{X}$ greater than 540?
        8.2.3. Perform z test:
            8.2.3.1. $\bar{X} - \mu$ / standard error of $\bar{X}$
            8.2.3.2. Standard error of $\bar{X} = \sigma$ / square root of n.
        8.2.4. Look at obtained z score on Unit Normal Table

9. Conclusion and Summary
   9.1. The distribution of sample means is a theoretical construction of all possible samples from a population.
   9.2. The Central Limit Theorem states that the distribution of sample means will be normal if the population is normal and if $n \geq 30$.
   9.3. The average of the distribution of the sample means is referred to as the expected value of $\bar{X}$ and is a measure of central tendency.
   9.4. The standard deviation of the distribution of the sample mean is referred to as the standard error of $\bar{X}$ and is a measure of variability.
   9.5. Basic hypothesis testing using the distribution of the sample mean uses the following formula for a z score:
      9.5.1. $\bar{X} - \mu$ / standard error of $\bar{X}$, where the standard error of $\bar{X} = \sigma$ / square root of n.

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