Application of an Online Reference for Reviewing Basic Statistical Principles of Operating Room Management

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Abstract

Operating room (OR) management differs from clinical anesthesia in that statistical literacy is needed daily to make good decisions. Two of the authors teach a course in operations research for surgical services to anesthesiologists, anesthesia residents, OR nursing directors, hospital administration students, and analysts to provide them with the knowledge to make evidence-based management decisions. Some of these students do not remember enough of their basic statistics class(es) to understand the principles presented. We performed a systematic, qualitative survey of previous experimental and quasi-experimental studies of the impact of a computer on student learning of the basic statistical topics that form a prerequisite to the management course. Computer-assisted instruction enhanced student learning of the basic statistical topics.
We created slides containing both hyperlinks to specific pages of Rice University's introductory-level free web-based "Online Statistics Book" and OR management examples to provide context

for the material. The website is effective at teaching the material because it directs students to test their predictions, which has been shown to enhance learning. Once students have completed the statistics review, they have sufficient background to learn the material in the OR management course. The students use an interactive Excel spreadsheet dealing with OR management topics to provide additional computer-assisted instruction.

1. Introduction

Anesthesiologists are integrally involved in operating room (OR) management (Marjamaa and Kirvela, 2007), and describe coordination of surgical suites and smooth patient flow as part of their professional work (Larsson, Holmström, and Rosenqvist, 2003). However, OR management differs from clinical anesthesia in that statistical literacy and reasoning are needed to make good decisions. Management decisions are made years, months, and days before surgery, as well as on the day of surgery. Optimal decisions cannot be made in any time frame without applying statistical knowledge (Dexter, Epstein, Traub, and Xiao, 2004; Dexter and Ledolter, 2005; McIntosh, Dexter, and Epstein, 2006; Dexter, Willemsen-Dunlap, and Lee, 2007; Pandit and Dexter, 2009; Dexter et al., 2009). Studies at two hospitals showed that the knowledge needed to apply relevant statistically-based operations research / management science was not learned on the job (Dexter, Willemsen-Dunlap, et al., 2007; Dexter et al., 2009). The operations research knowledge must be learned by study (Dexter et al., 2009). Psychological biases cause OR managers to neglect statistical facts (e.g., incidences of ORs finishing early), resulting in suboptimal decisions months before surgery (Wachtel and Dexter, 2010), days before surgery (Dexter, Xiao, Dow, Strader, Ho, and Wachtel, 2007; Dexter et al., 2009), and on the day of surgery (Dexter, Lee, Dow, and Lubarsky, 2007; Stepaniak, Mannaerts, de Quelerij, and de Vries, 2009; Ledolter, Dexter, Wachtel, 2010). For example, when planning staffing months in advance, decision-makers inappropriately focus on mean demand rather than upper quantiles and rely disproportionately on the most recent demand values (Wachtel and Dexter, 2010).

Two of the authors teach a 35-hour course in operations research for surgical services, which lasts either 3.5 days or two successive weekends. We have taught it 14 times as of September 2010. The course teaches anesthesiologists, anesthesia residents, nurse managers, certified registered nurse anesthetists, analysts, and hospital administration students how to apply statistically-based operations research principles to OR management to make evidence-based decisions. See www.FranklinDexter.net/education.htm for the syllabus, lectures, readings, and case studies. After lectures, groups of two to three participants solve problems based on realistic case studies while we observe and assist. Prior to establishing a prerequisite of review of statistical principles, students struggled with the assigned questions. Even though all the students had once taken basic statistics, many had little functional skills in solving simple statistical word problems. Students with recent experience in statistics finished the questions much more quickly. We thus started encouraging a prior review of basic statistics.

Table 1 provides examples of OR management decisions, demonstrating how an understanding of statistics up to and including Student's *t* test is necessary for making the types of decisions for which OR managers are typically responsible. The decisions in the right-hand column were taken from the case studies and from the 1st, 2nd, and 3rd lectures of our OR management course.

Table 1 also shows topics in Rice University Online Statistics Interactive Multimedia Course that are needed to understand Student's *t* test (Lane, 1999; Lane and Scott, 2000). This introductory-level "Online Statistics Book" is free and public (http://OnlineStatBook.com, accessed July 14, 2010). Students read material from the Online Statistics course or listen to lectures, answer questions, and perform simulations demonstrating principles.

Table 1. Prerequisite Knowledge for Student's *t* Test in Our OR Management Course and Relationship to Topics in the Online Statistics Book

Topics listed in sequence of http://OnlineStatBook.com and their associated chapters	**Decisions made by operating room managers that make use of statistical topics**
Interpret probability distribution shown by cumulative frequency curve with right skew (Chapters 1-3)	Predict the time remaining in late running cases for assigning staff, moving cases, and scheduling add-on cases (Dexter, et al., 2004; Dexter and Ledolter, 2005; Dexter et al., 2009). The far right tail of the probability distribution curve influences the expected times remaining.
Understand central tendency, difference between mean and median, and absolute deviation; calculate mean, median, trimmed mean, percentiles, range, variance, standard deviation; and understand relationship between mean and variance (Chapters 1-3)	Schedule cases using either the mean, median, or trimmed mean of historical case duration data, all of which are reasonable (Dexter et al., 2004; Dexter and Ledolter, 2005). Monitor predictive error in time remaining in late running cases using the absolute deviation (Dexter et al., 2004; Dexter and Ledolter, 2005; Dexter et al., 2009).
Understand positive and negative correlation, linear correlation, and strength of relationships (Chapter 4)	Incorporate surgeon characteristics in predictions of case durations, for use in scheduling cases and in predicting the time remaining in late running cases. Patient and surgeon characteristics are positively correlated with case durations (Dexter et al., 2009).
Interpret probability, conditional probability, statistical independence, base rates, and Bayes theorem (Chapter 5)	Determine times patients should report for surgery so that OR waits for patients only 5% of the time, based on the probability that earlier cases may end sooner that predicted, since more than half of OR cases start early (Dexter and Ledolter, 2005; Wachtel and Dexter, 2007; Smallman and Dexter, 2010).
Understand normal distribution, area under normal distribution, differences among normal distributions, and standard normal distribution (Chapter 6)	Calculate appropriate hours of staffing for each specialty by day of the week based on mean and standard deviation of actual workload (McIntosh et al., 2006). Methods that rely on the total durations of workdays in ORs often follow normal distributions (McIntosh et al., 2006). The total hours for which staffing has been planned but no cases need to be done represents time available for other activities (e.g., meetings) and is estimated by using areas under the normal distribution curve (McIntosh et al., 2006).

Understand sampling distribution, sample size, and central limit theorem (Chapter 7)	Statistically compare mean operating room times among surgeons, for both common and uncommon combinations of procedures (Dexter and Ledolter, 2005; Dexter et al., 2009).
Understand parameter, degrees of freedom, bias, sampling variability, confidence interval, confidence interval for the mean, and Student *t* distribution (Chapter 8)	Calculate confidence intervals for differences between surgeons' estimates of scheduled durations and mean of historical case durations, to select interventions which reduce predictive variability of case duration estimates (McIntosh et al., 2006).
Understand P-value and one-tailed test (Chapter 9)	Calculate probability that one case will take less time than another for sequencing surgical cases, which relies on understanding interpretation of probability versus P-value. Methods are analogous to calculating P-values (Behrens-Fisher problem) (Dexter et al., 2004; Dexter and Ledolter, 2005). In addition, as each case is scheduled, calculate the probability that the surgeon's scheduled case duration estimate is significantly ($P < 0.05$) less than the mean of historical case durations (Dexter et al., 2009).
Understand and perform Student's *t* test for a mean, comparison of results for Student's *t* test and Z test, and Student's *t* test for two means (Chapter 10)	Use 90% upper prediction bounds to determine maximum duration of cases used to fill holes in OR schedule (Dexter et al., 2004). Since the logarithms of case durations tend to follow normal distributions, with unknown means and standard deviations, prediction bounds for case durations are based on Student's *t* distribution (Dexter et al., 2004; Dexter and Ledolter, 2005; Dexter, Epstein, et al., 2009).

We needed a tutorial so our students could review statistics prior to the OR management course. We sometimes do not even know participant names until a few days ahead of the course when the hospital or health system sends its list of attendees. We had to be able to reference the tutorial in course instructions sent to the hospital or health system. Often it is not feasible to provide instruction to each student on an individual basis. Enrollees would need to be sent to one of several online statistical tools (see e.g. Mills, 2002; Chance, Ben-Zvi, Garfield, and Medina, 2007 for lists of available online tools). Pooling results among many disciplines, computer-assisted instruction can achieve learning at least equivalent to instructor-given lectures (U.S. Department of Education, 2009). Consequently, we expected that the Rice Online Statistics Book would be satisfactory for our purposes.

We performed a literature review to assess the usefulness of online tools, and specifically the Online Statistics Book. Our two hypotheses were the following: 1) Online tools are an effective way to communicate the statistical principles that need to be reviewed by anesthesiologists to learn basic OR management. In other words, we would not have to perform our own studies to demonstrate the usefulness of online tools for review of those topics. 2) For those topics in Table 1 (e.g., sampling distributions) for which simulation has previously been shown to be efficacious for learning (i.e., statistically significant P-value for benefit), simulation would be included in the Online Statistics Book. If the hypotheses are satisfied, the implication would be that there is a free, web-based course sufficient to meet the statistical needs of anesthesiologists, anesthesia residents, and others who plan to learn and/or do OR management.

We subsequently describe our implementation of use of the Online Statistics Book, including characteristics of an interactive Excel workbook that provides adaptive elaborative feedback during the completion of our class' case studies.

2. Methods: Literature Review

On July 14, 2010, we searched PubMed, ISI Web of Knowledge, and ERIC (Education Resources Information Center) for (computer∗ OR e-learning OR simulation) AND (educat∗ OR learn∗ OR student∗ OR teach∗) AND (statistic∗) in the title of peer reviewed articles. The search was limited to titles, because including abstracts resulted in thousands of unrelated articles. No restriction was placed on language. We read all identified papers for which the abstract or title included any suggestion that the article satisfied our inclusion criteria: experimental or quasi-experimental study of the impact of a computer on student learning of a topic in Table 1. For inclusion, the computer group had to differ from the control group by using computer demonstrations, simulations, interactive exercises, and/or automatic feedback (i.e., not viewing PowerPoint slides online and/or listening to recorded lecture video versus being in a classroom). One or more of the topics in Table 1 had to be included. These criteria were used, because our students' review of statistical topics was going to be online and cover the material of Table 1 (see Discussion). The search identified six articles: A) Dimitrova, Maisel, and Persell, 1993; B) Ragasa, 2008; C) Su, 2000; D) Liu, Lin, and Kinshuk, 2010; E) Krause, Starka, and Mandl, 2009; and F) Basturk, 2005. From two review articles (Mills, 2002; Chance et al., 2007), we obtained three additional articles: G) Weir, McManus, and Kiely, 1991; H) Lane and Tang, 2000; and I) delMas, Garfield, and Chance, 1999. Reference review identified no more articles about topics in Table 1.

Results from the nine articles are summarized below. We refer to each of the studies by letters A-I at the starts of paragraphs. Studies A-H address Hypothesis #1 and studies H-I address Hypothesis #2.

3. Results: Summaries of the Studies

Study A) Undergraduate students who had not previously taken a statistics course were given background material (such as that covered in Chapters 1-3 of Table 1) followed by information regarding the sampling distribution of the mean (Dimitrova et al., 1993). Some students learned the material using a computer simulation program and others received the material via a classroom lecture. Both were presented during a single learning session. Twice as many students in the computer simulation group got the correct answer on the open-ended question on the quiz, suggesting greater understanding of the concepts. There was a trend for overall higher test scores in the computer simulation group, but the difference was not statistically significant. These results show that a single lesson with a computer may modestly enhance learning, but, if so, the effect is small.

Study B) Undergraduate students took a twelve-hour basic statistics course (Ragasa, 2008). After the first three hours of lecture, one group used self-paced computer instruction and worked in pairs for the remainder of the course, with an instructor available only for answering questions. The other group received more lectures and classroom assignments. The topics were those in Chapters 2 and 3 of Table 1. Students using computerized instruction increased their knowledge, as measured by comparison of pre- and post-test scores, significantly more than those in the traditional lecture group. In other words, a computerized curriculum without an instructor enhanced learning *more* than lectures. However, change in attitude toward mathematics was unaffected (Ragasa, 2008).

Some undergraduates in a basic statistics class may perceive they are learning principles that they will never use again. Consequently, it is unknown whether the result in Study B (Ragasa, 2008) of a lack of influence on attitude applies to students in OR management.

Study C) Senior undergraduate business school students were randomly assigned to one of three sections of a business statistics course. The sections were identical except for no, moderate, or extensive use of computer programs in the classroom throughout the semester-long course (Su, 2000). The extensive use group reported a significantly greater interest in the topic and greater understanding of the material.

Study D) Similarly, high school students studied linear correlation (Liu et al., 2010). The computer group made predictions, received automatic feedback, and experimented with simulations. The computer group learned significantly more than the control group that viewed lectures and read content.

Study E) Undergraduate students used a software package to learn correlation, as in the material from Table 1, Chapter 4 (Krause et al., 2009). In this two by two design, students worked in pairs or as individuals. The software used in this study either had adaptive elaborative feedback regarding each question in a multiple-choice test, or simply a solution that the students could compare to their own answer. Students presented with the more elaborate feedback scored higher on the post-test than students who had only solution feedback. However, working in pairs did not improve post-test scores, and, among students in the feedback group, those who worked in pairs had worse learning than students who worked as individuals. Finally, the study found that students with lower baseline knowledge were the ones who gained the most in the elaborated feedback condition.

An implication for anesthesiologists, anesthesia residents, etc., from Study E (Krause et al., 2009) is that working alone and using the Online Statistics Book with its feedback to each question is not a significant disadvantage. In addition, the Online Statistics Book is likely to be effective for those anesthesia learners who do not currently perform statistical analyses as part of their work.

Study F) Undergraduate students in an introductory statistics course either had lecture plus typical statistics homework problems or lecture plus computer-assisted instruction (e.g., calculating means and creating frequency distributions) (Basturk, 2005). Computer-assisted instruction resulted in overall increased learning, as demonstrated by midterm and final exam scores. For topics from Chapters 1-3 in Table 1, the increase in test scores was statistically significant, but small. For topics from Chapters 7-10, there were greater benefits from the computer-assisted learning than for Chapters 1-3. The importance of these findings for our application is two-fold. First, as found in the preceding Studies B and F (Ragasa, 2008; Basturk, 2005), increased computer use enhances learning. Second, learning is enhanced even more for topics that rely on sampling distributions (Table 1, Chapters 7-10).

It is well documented that students struggle with learning sampling distributions (Weir et al., 1991; delMas et al., 1999; Lane and Tang, 2000). Anecdotally, we have repeatedly observed in our class students who can substitute numbers into the formula for 95% upper confidence bound for the mean, but cannot apply that knowledge. For example, they cannot give a meaningful explanation as to why they are using Student's *t* distribution (e.g., to predict the end of the workday in an OR) when the underlying probability distribution (e.g., for total hours of cases) follows a normal distribution. They cannot explain why, if 7 hours is the 95% upper confidence limit for the mean total hours of cases including turnovers and the OR day starts at 7:00 AM, the OR finishes after 2:00 PM on more than 5% of the days (i.e., they inappropriately apply confidence limits when they want prediction limits). The remaining three studies specifically assessed the learning of sampling distributions.

Study G) Students in a second year statistics class viewed a lecture that included a presentation of graphic animations of concepts (e.g., sampling distributions for the mean, as shown in Chapter 7 of Table 1). The students then either interacted or did not interact with the demonstrations (Weir et al., 1991). Students using the interactive exercise scored better on routine course tests than students without the interactive exercise, especially those students considered "lower ability" based on their first year statistics course score. The authors' qualitative impression was that learning was enhanced because the students had control over the demonstration material and were able to practice the concepts more at their own pace.

The implication of Study G (Weir et al., 1991) for students of OR management is that interactive simulation, as in the Online Statistics Book, is likely important for review of basic principles of sampling distributions, especially for those students with limited recent (prior) statistics training.

Study H) Students were recruited for a psychology experiment and told it concerned general cognitive ability (Lane and Tang, 2000). There were three groups of students: no training (control), training on sampling distributions for uniform distributions via textbook examples, or training by watching a computer simulation projected in front of the classroom. Students trained with the computer simulation correctly answered more questions from different applications than did students trained with textbook examples, and both answered more questions correctly than did students in the control group.

Study I) Students in introductory statistics classes used a sampling distribution simulation program as ancillary instructional material (delMas et al., 1999). The program permitted students to choose the shape of the probability distribution and then draw many samples from it, using different sample sizes. Simply using the simulation program did not substantively improve student performance (i.e., absolute increase of 8% in correct answers from pretest). In contrast, a separate group of students first took a pretest in which they made predictions about answers.

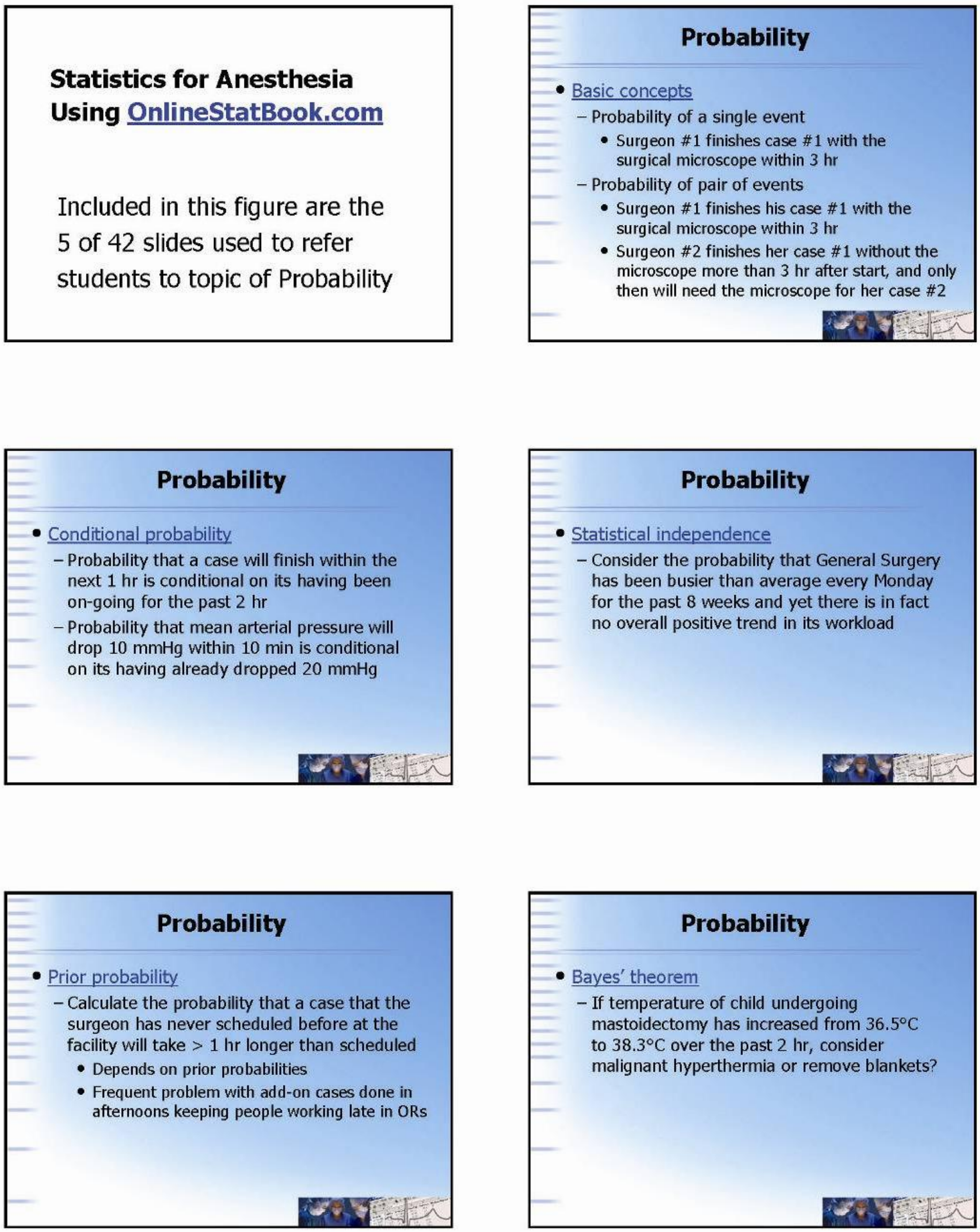
They then used the simulation to test their hypotheses and evaluate their responses. Post-test performance was markedly improved (i.e., absolute increase of 56% in correct answers).

The implications of Studies H (Lane and Tang, 2000) and I (delMas et al., 1999) are that inclusion in the Online Statistics Book of sampling distribution simulations is likely to support learning that anesthesiologists, anesthesia residents, etc., can apply from the example problems to applications in OR management. Lecture and simulation alone are less likely to provide the skills for learning OR management. Student misconceptions ideally are revealed and addressed, as done by the Online Statistics Book.

4. Application: Outline of the Course

Anesthesiologists, analysts, nursing directors, and hospital administration students have used the Online Statistics Book at a self-regulated pace (via Table 1) to review basic statistics prior to participating in our OR management course. No instructor time is required for the statistics review, thereby reducing training costs. The students access the web material via a set of 42 customized slides that provide examples relevant to anesthesia and OR management. The slides have been saved as an Acrobat PDF file, which is publicly available at www.FranklinDexter.net/education.htm (see “1. Statistics for Anesthesia”). Each slide has one link to a specific web page of the Online Statistics Course. The students can navigate the relevant portions of the site by following our sequence of slides. Figure 1 shows the five slides used for the topic of probability.

Figure 1. The five of 42 successive slides used to refer the management students to the topic of probability.



Each slide contains a hyperlink to a web page, demonstration, etc., from the Online Statistics Course.

After the statistics review, students take the course in scientific principles of operating room management (see www.FranklinDexter.net/education.htm for details). The 3.5 day course includes ten lectures, seven published articles, and 17 case studies with 156 problem-solving exercises, many of which are word problems. For example, Table 2 is a case study involving use of the cumulative normal distribution. At the start of the first day, the team predicts the answer to a similar question. The case is presented on the second day of the course, when the team can reconcile their earlier prediction with the correct answer. In the case study, students use material learned in lecture and readings on how to plan staffing to minimize the inefficiency of use of operating room (OR) time. The inefficiency of use of OR time is a weighted combination of the expected hours of under-utilized OR time and the more expensive expected hours of over-utilized OR time. Under-utilized OR time occurs on days when realized workload (i.e., total hours of cases including setup and cleanup times) is less than planned staffing. Over-utilized OR time occurs when workload exceeds planned staffing and staff must work late. Over-utilized time should occur on less than 1/3 of days if staffing is planned and cases are scheduled based on minimizing the expected value of the inefficiency of use of OR time (Strum, Vargas, May, and Bashein, 1997; Dexter and Traub, 2002; Dexter et al., 2004; McIntosh et al., 2006; Dexter, Willemsen-Dunlap, et al., 2007; Pandit and Dexter, 2009; Stepaniak et al. 2009; Smallman and Dexter, 2010; Wachtel and Dexter, 2010). Question (a) highlights that if cases are not scheduled sequentially, even a perfectly predictive forecast of OR workload is not a good estimator for the end of the workday (Dexter and Traub, 2002). Subsequent questions show that each increase in the standard deviation of workload results in an increase in appropriate staffing (Strum et al., 1997; Pandit and Dexter, 2009).

Table 2. Portions of Case 6 of a total of 17 cases from the Operating Room (OR) management course, with answers to be entered into the Excel workbook shown in Figure 2.

On Mondays, the total hours of orthopedic cases including turnovers follow a normal distribution with a mean of 30 hours. Use this value for (a) to (f).

a) Suppose that no rules were set for case scheduling. Staffing is planned for (i.e., OR allocations are) 10 hours per OR per day. For this first question (a), make the simplifying assumption that all Mondays are identical. The standard deviation of total hours of orthopedic cases including turnovers is 0 hr on Mondays. Yet, on average, there are 5 hours of under-utilized OR time and 5 hours of over-utilized OR time for orthopedics on Monday. How is this possible? Recall that if staff scheduling matches the staffing, then the 5 hours of under-utilized time would result in staff being scheduled but without cases to do and the 5 hours of over-utilized time would result in staff working late beyond their scheduled hours. The answer shows why rules are indeed set for case scheduling.

b) For questions (b-f) below, you should realistically assume that cases are scheduled based on minimizing expected over-utilized OR time. The relative cost of an hour of over-utilized OR time is twice the cost of an hour of under-utilized OR time, meaning that the probability that the day ends early equals 2/3. For this second question (b), again assume that the standard deviation of orthopedics' workload on Mondays is 0 hours. What OR allocation for orthopedics on Mondays would result in maximal efficiency of use of OR time? First, determine how many hours of orthopedic cases are performed each Monday. Then, plan your staffing (OR allocation) while considering both 8 hours and 10 hours workdays, to make up your 40 hour week (5×8 hours = 4×10 hours). Do not answer twice, once for 8-hour workdays and another for 10-hour workdays, just consider that staffing for the mean of 30 hours can be a combination of the two.

c) Repeat question (b), but now set the standard deviation of the workload among Mondays to a realistic 5 hours. What would be the appropriate OR allocation? To perform the calculation, you will need to look up the inverse of the normal distribution. In Excel, you can use "=NORMINV" function, with the mean of 30 hours and standard deviation of 5 hours. If you are not sure what to do with NORMINV, read the Help built into Excel and see what happens when you enter values for which you have previously learned the answers. You can figure out the percentile to use to answer this question from the preceding paragraph. Your appropriate OR allocation will be higher for (c) than for (b), because the standard deviation is higher for (c) than for (b).

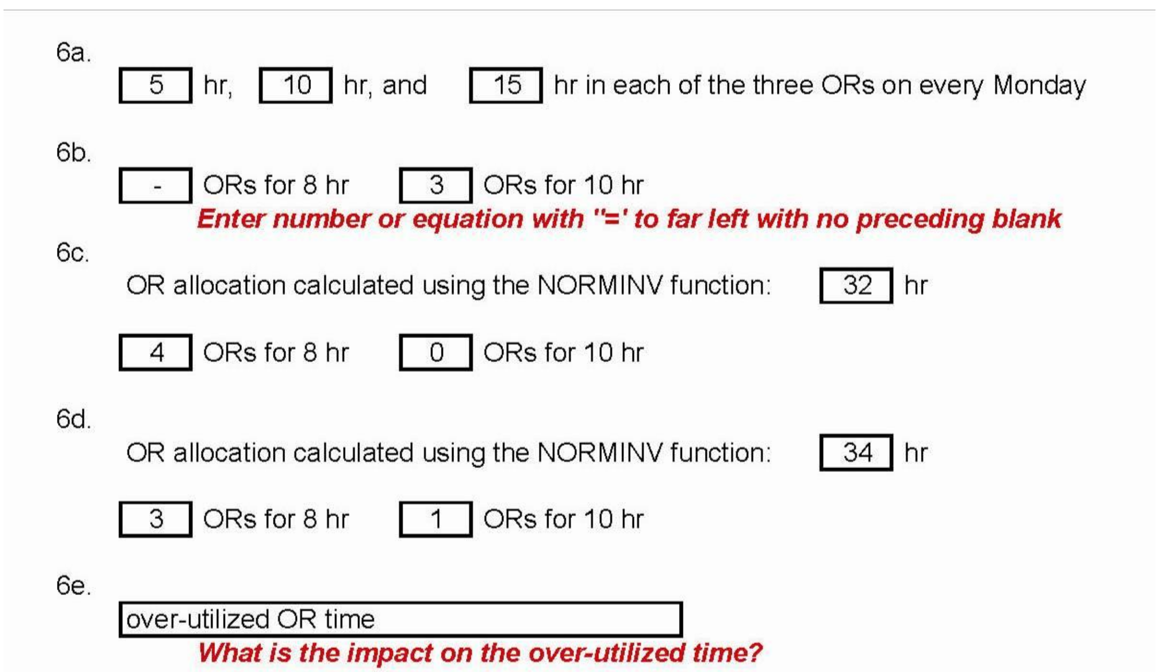
d) Repeat question (c), but now set the standard deviation to a large 10 hours. Just like for (c), you will need to use NORMINV to calculate the inverse of the normal distribution.

e) Why does it make sense that the allocation is larger if the standard deviation is larger, even though the mean is the same? In other words, why is the answer to (d) larger than (c), and why is the answer to (c) larger than (b)? The precise language matters, because you need to be able to explain the principle to stakeholders. "Rewarding" specialties that have larger variability with more staffing seems initially unfair to other stakeholders.

To accompany our case studies and related problem-solving exercises, we created an Excel workbook tool that provides immediate, adaptive, elaborated feedback to the numeric and short answer questions. An Excel workbook was chosen for completion of the case studies, rather than a web-based platform, because internet access has been consistently unreliable during our OR management course. We have given the course in hospitals and in hotels arranged by hospitals, and despite our instructions, have had spotty internet access or limited bandwidth when up to 40 users have logged in simultaneously. For example, during the latest course of 19 students, the hotel lost internet access for 1.5 days because of nearby construction. Since that course was given over 3.5 days, that was > 40% of its hours. In addition, students (i.e., anesthesiologists, nursing directors, and analysts) often lack administrative rights to change security settings on their computers, effectively precluding the use of Excel macros, or browser security settings. The workbook consists entirely of worksheet formulae that run on any platform under any settings.

Elaborated feedback consists of questions or statements designed to encourage the students to think about ways to solve the problem, programmed based on the findings of study E (Krause et al., 2009). The feedback is adaptive, varying based on the answers entered by the students. Feedback is programmed without macros by the use of more than 4250 Excel formulas containing more than 8300 Excel functions. Most of the functions are combinations of IF() and SEARCH(), where the latter is the case insensitive function that locates strings of characters within text. Figure 2 shows an example of two errors and the automated responses to the errors. The corresponding Excel code is in the Appendix.

Figure 2. Excel responses to case presented in Table 2.



In 6b, the answer is zero ORs for 8 hours and three ORs for 10 hours. Entering a "- " results in a message. In 6e, a correct answer would be "reduces over-utilized OR time." The Excel formulas check for and accept multiple synonyms of "reduce," including "cut," "decrease," "diminish," "lessen," "lower," "minimize," "shrink," and "trim". Entering any of these words yields a correct answer.

The corresponding Excel equations are available online.

As part of the class, students learn how to use publicly available databases for evaluating patients' length of stay (e.g., http://hcupnet.ahrq.gov/ accessed July 14, 2010). The students determine the mean length of stay after obesity surgery for US Medicare patients and for patients aged 65 years and older undergoing such surgery in US non-federal hospitals. Lengths of stay are not the same for the two groups, and the question asks why. The correct answer is that there are many such patients receiving care who are not enrolled in Medicare. First, the workbook checks for an answer that is unnecessarily long, specifically > 133 characters. Second, the workbook checks that the word "Medicare" is present in the answer. If not, feedback is provided re-phrasing the question and suggesting, "Start by specifying what insurance plan the question is asking about." Third, the workbook checks for permutations of the words, "covered," "enrolled," "have," "eligible," "entitled," and "qualified." If none is present, feedback is provided, again rephrasing the question, and explaining, "You need to know and state the relationship between Medicare and being 65 or older."

Before and after lunch, and for the last several hours of each day, students answer questions in the Excel workbook. One of the instructors is immediately available to answer questions and provide feedback. With each successive class, we have learned which incorrect answers are common and have modified the Excel automatic feedback to provide guidance.

5. Discussion

Prior work showed that anesthesiologists perceive OR management to be an integral part of their professional work (Marjamaa and Kirvela, 2007; Larsson et al., 2003). As reviewed in the Introduction, statistical methods are needed for good OR management decisions, and misconceptions that good decisions can be made absent statistical methods are due to psychological biases. Our course in operations research for surgical services teaches OR management, including when to apply different statistical methods, enabling anesthesiologists and other managers to make evidence-based decisions.

The current paper considers how to assist anesthesiologists and OR managers as they review the basic statistical methodology to learn scientific principles of OR management. Based on a systematic study of previous experimental and quasi-experimental studies, computer-assisted instruction has been found to enhance learning of the topics in Table 1 (Studies A-H), especially for sampling distributions (Studies F-H). Experiments, most with undergraduate students, showed that the students typically learned more with a computer-assisted curriculum. Hypothesis 1, the existence of such studies, is supported. Furthermore, the specific structure of the simulations in Rice University's Online Statistics Interactive Multimedia Course matches that which previous research has shown to have benefit (Studies H-I). Hypothesis #2 is supported. Specifically, for those topics in Table 1 (e.g., sampling distributions) for which simulation has previously been shown to be efficacious for learning, simulation is included in the Online Statistics Book.

We do not have the opportunity to interact with most of our students before they take our OR management course, because they are not enrolled in a program (i.e., they simply take the course). In addition, the topics in Table 1 are covered on the first day (i.e., they need to review before the course has started). Thus, an online version of review with little or no instructor involvement is appropriate. Because of this specific requirement, we chose to review articles that most closely match this particular learning situation. Since we do not teach a statistics review course, we did not include papers that studied online/ distance learning versus in-class learning. That topic was recently reviewed by Everson and Garfield, 2008. Generally, online teaching of introductory statistics can achieve comparable learning as traditional classroom teaching (e.g., see Utts, Sommer, Acredolo, Maher, and Matthews, 2003; Lawrence and Singhania, 2004; and Dutton and Dutton, 2005). Conclusions are similar to those obtained for many fields combined (U.S. Department of Education, 2009). Instead, we surveyed experimental studies of computers being used for simulations, exercises, and/or feedback. Importantly, ***none*** of the nine articles we identified (A-I) was included in Everson and Garfield's 2008 survey. ***None*** of the 20 articles that they referenced as studies of online learning met our inclusion criteria. The lack of overlap between references shows that indeed the topic that we surveyed differs from the topic of online versus in-class learning. The fact that we limited consideration to computer simulations, etc., may explain why Everson and Garfield's findings were more modest than our conclusions.

Another reason why our conclusions may differ from studies of online courses versus traditional classroom teaching is that among the articles we identified, only two included classes lasting several months (studies C and F). The other studies involved experimental sessions with a median duration of about 1.5 hr: H) 0.5 hr, G) 1 hr, D) 1.5 hr, I) 1.5 hr, E) 3.5 hr, A) 5 hr, and B) 12 hr). These brief sessions are appropriate for examining the efficacy of learning techniques for our OR management students, since they are generally reviewing statistics for several hours.

A limitation of the list of topics in Table 1 is that it does not include instruction in recognizing the key points in statistical word problems (Quilici and Mayer, 2002). Students struggle with solving word problems (e.g., whether the dependent variable is continuous or categorical; whether there is one group, two groups, or more groups; and whether the probability distribution is normal). Because recognition of a problem's structure is a skill that is taught (Quilici and Mayer, 2002), and most OR management issues are word problems, we have tried to make techniques for solving word problems a focus of the assignments in our management class. Even if such word problems were in the Online Statistics Book, the problems would have little contextual advantage for our students because the Book's examples are designed for undergraduate psychology majors rather than anesthesiologists and nurse managers.

Another limitation of the content of the Online Statistics Book listed in Table 1 is that the topics are relevant to the OR management, but not to reading the anesthesia literature in general. Windish, Huot, and Green, 2007 categorized and counted the statistical methods used in original research articles in six general medical journals (e.g., New England Journal of Medicine) published in the first quarter of 2005. Student's *t* test was used in 20% of these papers, while more sophisticated methods were used more often (e.g., multivariate statistics 69%, Cox proportional hazards model 27%, and multiple logistic regression 23%). Each of these methods is typically taught as its own single semester course. Anesthesia journals have far more mathematics (e.g., because of extensive use of nonlinear mixed effects modeling and Bayesian methods for target controlled drug administration). Thus, the material contained in Table 1 is far too basic for anesthesiologists and other health professionals who need to evaluate clinical trials critically. Journal club learning alone can increase resident knowledge of research methods and statistical analyses, but is insufficient to teach the statistical methods (Moharari, Rahimi, Najafi, Khashayar, Khajavi, and Meysamie, 2009). For example, considerable background knowledge is needed to critique a Cox proportional hazards model with propensity score as an independent variable. On the other hand, a curriculum of broad statistical principles, including monthly lectures over a year, with corresponding monograph, problem solving, and manuscript review, was found to enhance learning for residents as measured by comparing pre- and post-test scores (Cheatham, 2000). The implication of these results is that, although the contents of Table 1 seem sufficient as prerequisite to learn how to make good OR management decisions months, weeks, or days in advance (Dexter et al., 2004; Dexter, Willemsen-Dunlap, et al., 2007), future evaluation of strategies for educating anesthesia providers in statistics for other applications would be useful.

Finally, a limitation of our course is that it is small and thus there are too few evaluations to be of scientific value. In the latest class, two anesthesiologists, two hospital administrators, one OR nursing director, and four industrial engineers reported using the statistics review. The students were asked to agree or disagree with various statements on a five-point scale, with four being "agree" and five being "strongly agree." All of the students scored the course a four or five with respect to "course was well planned and content was organized logically," "cases and readings aided in learning the material," "class increased my trust in applying evidence-based statistical methods and analytic reports in healthcare management decisions," and the "class enhanced my ability to analyze managerial questions critically and solve the problems in a logical, evidence-based manner." Future work is needed to evaluate the impact of previous statistical training and knowledge on actual (not perceived) impact of the course.

Appendix

Excel hidden cells and formulas producing feedback to incorrect answers entered for questions 6b and 6e (Figure 2), with cell addresses modified for presentation

AA1 = IF(OR(ISERROR(Q6b_8hr), ISERROR(Q6b_10hr)), "Enter number or equation with "=' to far left with no preceding blank", "OK")

AB1 = IF(AND(0 = LEN(Q6b_8hr), LEN(Q6b_10hr) > 0), "Please enter a number in each space", "OK")

AC1 = IF(OR(0 = LEN(Q6b_8hr), 0 = LEN(Q6b_10hr)), "", "OK")

AD1 = IF(OR(NOT(ISNUMBER(Q6b_8hr)), NOT(ISNUMBER(Q6b_10hr))), "Enter number or equation with "=' to far left with no preceding blank", "OK")

AE1 = IF(OR(Q6b_8hr < 0, Q6b_10hr < 0), "Value cannot be negative", "OK")

AF1 = IF(OR(Q6b_8hr <> INT(Q6b_8hr), Q6b_10hr <> INT(Q6b_10hr)), "Numbers of ORs are whole numbers.", "OK")

AG1 = IF(30 <> 8*Q6b_8hr + 10*Q6b_10hr, "The mean should equal 6A answer of 30 hours", "")

AH1 = IF(AA1 <> "OK", AA1, IF(AB1 <> "OK", AB1, IF(AC1 <> "OK", AC1, IF(AD1 <> "OK", AD1, IF(AE1 <> "OK", AE1, IF(AF1 <> "OK", AF1, AG1))))))

BA1 = IF(0 = LEN(Q6e), "", "OK")

BB1 = IF(43 < LEN(Q6e), "Please shorten your answer - 4 or 5 words are sufficient", "OK")

BC1 = IF(OR(NOT(ISERROR(SEARCH("over-utilization",Q6e))), NOT(ISERROR(SEARCH("over utilization",Q6e))), NOT(ISERROR(SEARCH("overutilization",Q6e)))),"Be precise in your terminology. That is not the correct word.", "OK")

BD1 = IF(AND(ISERROR(SEARCH("over-utilized",Q6e)), ISERROR(SEARCH("over utilized",Q6e)), ISERROR(SEARCH("overutilized",Q6e))), "Focus on benefit accrued by increasing allocations when variability increases", "OK")

BE1 = IF(AND(ISERROR(SEARCH("cut",Q6e)), ISERROR(SEARCH("decrease",Q6e)), ISERROR(SEARCH("diminish",Q6e)), ISERROR(SEARCH("lessen",Q6e)), ISERROR(SEARCH("lower",Q6e)), ISERROR(SEARCH("minimize",Q6e)), ISERROR(SEARCH("reduce",Q6e)), ISERROR(SEARCH("shrink",Q6e)), ISERROR(SEARCH("trim",Q6e))), "What is the impact on the over-utilized time?", "OK")

BF1 = IF(BA1 <> "OK", BA1, IF(BB1 <> "OK", BB1, IF(BC1 <> "OK", BC1, IF(BD1 <> "OK", BD1, IF(BE1 <> "OK", BE1, "")))))

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