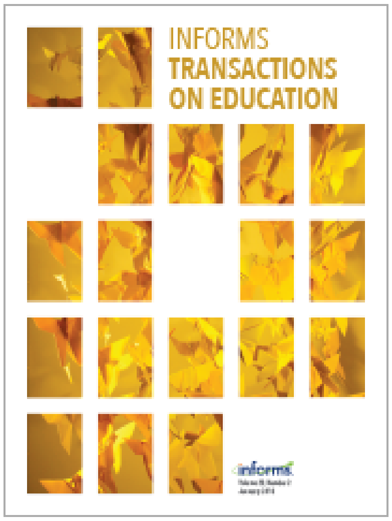

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How Big Should My Dot Be? Using Spreadsheet Simulation to Evaluate Process Improvement Data Collection Strategies

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Abstract. Occasionally, healthcare professionals approach analytical topics and courses with a blend of fear and loathing. They may fail to grasp the connection between particular principles and their application to actual process analysis and improvement. The run chart is a persuasively powerful quantitative tool. Healthcare teams could use this tool to better comprehend the extent of process changes over time. Although constructing the run chart is mathematically simple, healthcare professionals may be uncertain as to sample size sufficiency. They may also be unsure of the number of observations required in run chart subgroups. We developed a spreadsheet simulation model to provide enhanced relevance for the topic of run chart subgroup size determination. This classroom-tested active learning exercise helps healthcare teams to visually understand the relationships between subgroup size, underlying process variation, and anticipated levels of improvement.

Supplemental Material: The spreadsheet tool is available at https://doi.org/10.1287/ited.2016.0160.

Keywords: spreadsheet simulation • run charts • process analysis • process improvement

1. Introduction

Regrettably, some healthcare professionals participating in our executive education workshops, as well as students enrolled in degree-level programs, are not enamored with analytical topics and courses. Despite an instructor's best intentions and careful preparation, the approach of students or healthcare workers to our material may range from passive indifference to outright fear and loathing.

For nearly two decades, however, educators have touted the use of spreadsheets as a pedagogical tool that can bolster the appeal of our courses and illustrate mathematical material in a user-friendly environment (Powell 1997; Grossman 2002, 2006; Tsai and Wardell 2006). Indeed, a host of textbooks clearly conveys the application of spreadsheet model-building skills in operations analysis and decision making (Albright and Winston 2015, Ragsdale 2012).

Against this backdrop, we developed a spreadsheet tool[1] to analyze important statistical concepts in run charts. The run chart tool can be used in process studies to illustrate trends in data over time and to provide evidence of statistically significant change (Murray 2006, Provost and Murray 2011). A run chart "dot" represents actual process performance (for example, average waiting time in an emergency department). In our experience interacting with healthcare professionals in actual process improvement projects, the run chart emerged as an important tool in documenting deliverables and illustrating improvement. Such tools are used on hospital "visibility walls" to provide a transparent assessment of organizational performance. From a practical perspective, an important issue is the number of observations, also known as "subgroup size," that decision makers should use for each dot. A larger subgroup size may provide greater confidence in the process analysis, but could come at the expense of considerable data collection time and effort. To our knowledge, there are no published studies in the healthcare process improvement literature attesting to the faulty conclusions obtained via improper sample sizes. However, Button et al. (2013) document the pervasive problems created by low sample sizes in several neuroscience studies.

Although healthcare professionals and college students can be taught these concepts through algebraic manipulation of the sample size expression, we felt they would be better served by a tool that could simulate run chart behavior and visually display the impact of particular subgroup size strategies. Ultimately, we perceived that "plugging and playing" with a spreadsheet simulation model would be especially beneficial for our students and workshop participants.

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We have successfully used this tool for introductory quantitative methods/operations management courses and for executive education (e.g., healthcare professionals attending clinical practice redesign courses). For instance, we featured these spreadsheet simulation models in several iterations of "Principles of Measurement" workshops and "Quality Improvement Consultant" seminars delivered throughout Saskatchewan, our Canadian province. During these sessions, this tool was used with other process improvement or systems analysis approaches (e.g., handling conflict resolution, the lens of Profound Knowledge (NHS Scotland 2016, etc.)) to facilitate increased knowledge of and appreciation for quality improvement methodologies. Each of our seminars or workshops included dozens of healthcare professionals (e.g., nurses, Lean process improvement analysts, doctors). These learning opportunities were regularly delivered in various provincial health regions. Although we did not administer participant tests to evaluate conceptual knowledge or analytical understanding, each seminar or workshop included an in-depth evaluation instrument. Participant feedback was uniformly strong about the relevance, value, and importance of our workshop pedagogy, including the run chart spreadsheet simulation tool.

Note that our spreadsheet approach could also be worthwhile for those instructors teaching Lean/Six Sigma concepts (George 2002), since measurement and analysis play a critical role in the Six Sigma philosophy; one cannot improve what one cannot measure. Lean/Six Sigma principles are commonly applied in healthcare (Inozu et al. 2012). Moreover, the depiction of statistically significant changes available in run charts could fuel students' awareness of and appreciation for an important issue in control charts, i.e., the adoption of two versus three sigma limits. The choice of particular sigma limits can influence identification of special cause variation, analogous to the manner in which different subgroup sizes in run charts can illustrate changes in process behavior.

To the best of our knowledge, no other authors have developed such a spreadsheet approach to simulate subgroup size. Although the references are rather dated, note that Black (1999) used a spreadsheet simulation to illustrate the impact of sample size, standard deviation, and other parameters on statistical power; Jokinen (1995) created a spreadsheet tool for statistical process control.

The remainder of our paper is organized as follows. In Section 2, we demonstrate the specifics of run charts and describe how they provide evidence of statistically significant change. We also cover the manner in which we built our spreadsheet simulation model. In Section 3, we provide simulation model screenshots for determining subgroup size with two particular random variables, i.e., a continuous distribution (Normal) and a discrete distribution (Poisson). We offer some closing remarks and directions for further study in the concluding section.

2. Run Charts

A run chart is a line graph of data plotted over time. It enables one to visualize the flow of data and is an especially important tool in documenting process analysis and improvement activities. Although it can detect evidence of statistically significant change, it cannot distinguish between special and common cause variation as is the case with control charts.

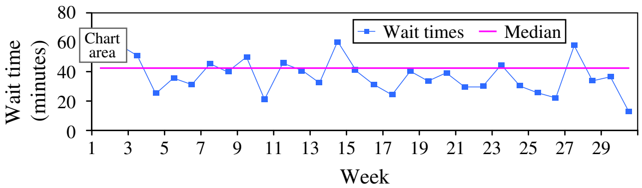
When the basic features of run charts are presented in our quantitative methods or executive education courses, a vital question concerns the number of observations to include in each run chart dot. In other words, should a decision maker create a chart in which dots represent individual occurrences, or should the dots correspond to an average of a particular number of data points? In our experience, class participants can recite the benefits and drawbacks of larger subgroup sizes, but seem uncertain as to the impact of underlying process variation on subgroup size decisions. We created our spreadsheet simulation tool to address this problem.

Note that, for an academic audience, development of a spreadsheet tool with associated simulation capabilities may seem a trivial exercise. Besides, subgroup size principles could be demonstrated with sample size equations. However, based on our experience in actual classroom settings, students' interest in the material is heightened when the spreadsheet approach is introduced. The ability to "plug and play" with a spreadsheet model and subsequently observe the impact of making parameter changes creates an active participant role for the healthcare professionals and students in our workshops and courses. The spreadsheet is seen as less threatening than mathematical manipulation of esoteric phenomena. Anecdotally, we noted that students relished the opportunity to be "in control" when it came to inserting different subgroup sizes (through the various shortcut keys) or requesting additional iterations (by hitting F9). The clear majority of our participants stated that algebraic equations (or even the background material on our model's "Calculations" sheet) were mathematically mysterious.

When developing a run chart, one typically calculates a median based on the first ten dots. As depicted in Figure 1, this median is then extended as a straight line through the run chart (this figure and all other run charts in this article are copied without modifications from the supplemental spreadsheet files). Ultimately, this median helps to clarify process improvement.

The determination of whether a run chart displays evidence of statistically significant change is made by evaluating at least three "rules." If any one of these

Figure 1. A Basic Run Chart



rules is met, then we can conclude that a statistically significant change has occurred. The first rule is denoted by a shift in the run chart; this is defined by six or more consecutive points all above or all below the median. The second rule explores the trend in a run chart, and is given by five or more points all going up or all going down. Finally, the "runs" rule calculates the number of times the run chart crosses the median. By comparing this value to an upper and lower limit (based on the number of plotted points in our run chart), we can detect whether there are "too few" or "too many" runs. Having too few or too many runs would signal that "something has happened" and that there is evidence of a statistically significant change.

To create a more participatory learning environment for understanding subgroup size issues, we created a spreadsheet run chart that plotted points for 30 weeks of data. We have used four different probability distributions for the underlying parameter of interest (Normal, Poisson, Lognormal, and Binomial). For our purposes here, we concentrate on the Normal and Poisson distributions.

Figure 2 shows a screenshot from our Normal distribution spreadsheet model. Students are asked to input the mean and standard deviation of a random variable. They also enter the week when the change occurs as well as the anticipated improvement (in terms of a decrease in the process mean) that this change will generate. In the example provided in Figure 2, the change occurred in week 15 (halfway throughout the 30-week run chart period) and resulted in a 30% reduction in the process mean. Color and borders are used to highlight the input that workshop or class participants need to provide. The "Calculations" sheet provides Normal probability distribution computation details.

Using the mean and standard deviation chosen by the student, the spreadsheet simulation model draws a value from that distribution. For each of the 30 weeks in our run chart, we simulate 30 individual observations (we chose 30 individual observations since this represents the largest subgroup size in our simulation model). Because some students or healthcare professionals may select a large value of the standard deviation relative to the mean, and thus obtain negative values for the variable of interest, our model replaces such negative values with 0. Following typical practice, the median is calculated on the data from the first 10 weeks of the run chart.

We set up Excel macros to model specific subgroup sizes (1, 2, 5, 8, 10, 15, 20, 25, and 30) that represented a reasonable variety of groupings. Moreover, we made these subgroup sizes accessible through various shortcut keys. By selecting a different shortcut key, students can represent different subgroup size strategies. Table 1 provides the shortcuts for each subgroup size (this information is also provided in the spreadsheets). We opted for these pre-selected groupings since most of our

Figure 2. Spreadsheet Screenshot—Normal Distribution

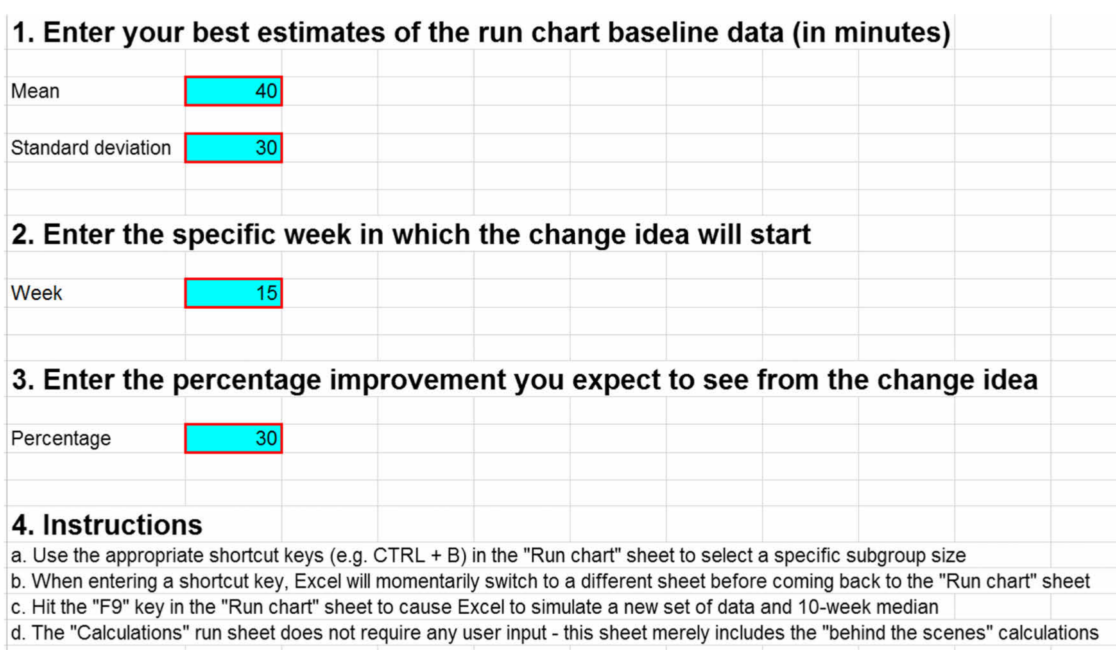


Table 1. Shortcut Keys for Various Subgroup Sizes

Shortcut keys	Subgroup sizes
CTRL + B	1
CTRL + E	2
CTRL + I	5
CTRL + J	8
CTRL + K	10
CTRL + M	15
CTRL + Q	20
CTRL + T	25
CTRL + Y	30

healthcare workshop participants did not have the necessary spreadsheet skills to develop their own macros.

Of course, students can simulate repeated draws with the same subgroup sizes by hitting "F9." We have found this feature to be especially motivating for obtaining and retaining participant interest.

In Figure 3, we provide a screenshot from our Poisson distribution spreadsheet model. The Poisson distribution could be especially useful for stochastic events that occur in discrete quantities (e.g., patient falls, medication errors). This spreadsheet asks healthcare professionals or students to enter the baseline occurrence rate for the event. As with the Normal distribution version, participants input the week when the change occurs as well as the anticipated improvement (in terms of a decrease in the rate of occurrence) generated by the change. In the instance depicted in Figure 3, the change occurred in week 15 and resulted in a 40% reduction in the event rate. In keeping with the Normal distribution spreadsheet, we adopted colors and borders to signify the input that participants need to provide. This spreadsheet includes two sheets ("Calculations" and "Poisson distribution") featuring detailed workings of the Poisson computations. No user input is required on those two sheets. Although these sheets are included "behind the scenes," we have found that the more advanced participants may appreciate details on the inner mechanisms of such calculations.

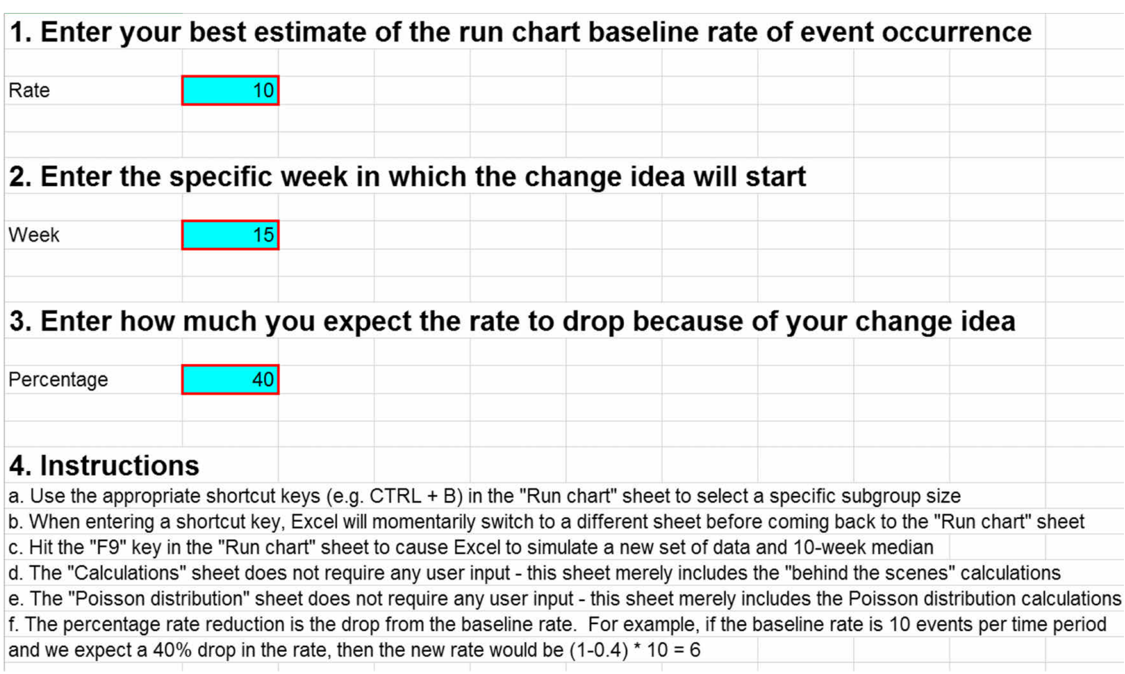
Similar to the Normal distribution case, we used the same set of Keys (Table 1) for the various Poisson subgroup sizes.

3. Spreadsheet Model Results—Normal Distribution

Apart from capturing some student interest, our other objective was to create a tool to demonstrate the practical implications of data collection. Based on particular values for the underlying process variation, the projected levels of improvement, and selected subgroup sizes, when could a decision maker be confident that they have collected "enough" data? (As previously described, these issues could be addressed through a statistical calculation, but the value of visibility provided by a spreadsheet simulation model could promote enhanced student understanding).

Decision makers could recognize that they have gathered enough data, i.e., that their dot includes a sufficient number of data points, when increasing subgroup sizes yield similar run chart behaviors. If they obtained very similar run charts for subgroup sizes of, say, 10 and 20 data points, then they could be confident that collecting 20 data points in each dot is

Figure 3. Spreadsheet Screenshot—Poisson Distribution



probably unnecessary. In other words, the larger subgroup size of 20 points provides similar conclusions as that obtained with the smaller subgroup size. If the goal is to obtain the "best bang for the buck," then using the smaller subgroup size may be warranted. On the other hand, if a smaller group size displays a relatively large amount of variability in a run chart (thereby making it more difficult to ascertain via the run chart rules that a statistically significant change has occurred), then a larger subgroup size would be preferred.

In Figures 4–6, we provide the results for different subgroup sizes in the case of a Normal random variable with a mean of 40 and a standard deviation of 30. The anticipated change (30% reduction in process mean with no change in the process standard deviation) was allowed to occur in week 15. We arbitrarily selected the vertical axis label "Emergency Department (ED) process wait time" for these run charts.

Figure 4 depicts the results for a subgroup size of 1. In this example, there is considerable variability before and after week 15 (the week in which the change occurred). Although one could use the shift rule to detect statistically significant change (since there is a string of at least 6 consecutive points after week 15 that are below the median), the variability of data points in the latter stages of the run chart may be troubling. Opting for a subgroup size of 1 may not provide the

Figure 4. Subgroup Size of 1—Normal Distribution

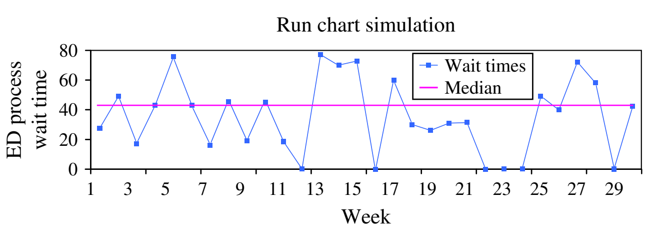


Figure 5. Subgroup Size of 10—Normal Distribution

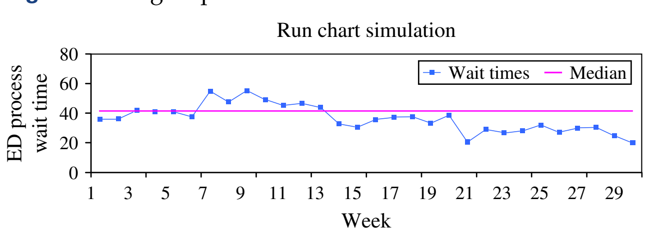
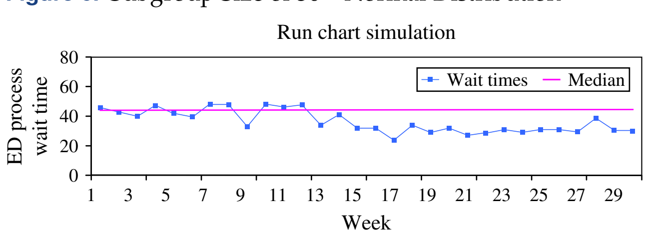


Figure 6. Subgroup Size of 30—Normal Distribution



precision one needs when using run charts to analyze process improvement. (Reminder: The example cited in Figure 4 is but one replication of a simulation model. Obviously, one would need to perform multiple replications to draw statistically valid conclusions).

Continuing with the same mean and standard deviation values as those used in Figure 4, we next ran a run chart simulation model with a subgroup size of 10. Results are reported in Figure 5. It is fairly obvious that the 30% reduction in the process mean occurring in week 15 has resulted in a shift in the run chart. Each point on the run chart from week 15 and onwards is below the median, thus providing evidence of a statistically significant change in our process. Moreover, our subgroup size of‘10 provides a fairly consistent set of points in the second half of the run chart.

In Figure 6, we illustrate use of a subgroup size of 30 (again with the same mean and standard deviation values as used in the previous screenshots). In this example, the reduced variability is even more pronounced. The shift in the run chart is still apparent. Because use of a subgroup size of 10 or 30 may lead one to draw similar conclusions, opting for the larger subgroup size may be unnecessary.

3.1. Spreadsheet Model Results—Poisson Distribution

Next we present a spreadsheet simulation example featuring the Poisson distribution. In this instance, we model different subgroup sizes in the case of a Poisson random variable with a rate of 10. The anticipated change (40% reduction in rate) was allowed to occur in week 15.

Figure 7 depicts the results for a subgroup size of 1. This example provides evidence of a statistically significant change in the process since all the data points (post week 15) fall below the median. Therefore, choosing a subgroup size of 1 may be sufficient. As described earlier, however, this is but a single replication of one simulation model. In practice, a decision maker would want to generate several replications to create informed conclusions.

Figure 8 illustrates a subgroup size of 5. The data point pattern after week 15 appear similar in form to the representation in Figure 7. Consequently, this could suggest to a decision maker that subgroup sizes of 1

Figure 7. Subgroup Size of 1—Poisson Distribution

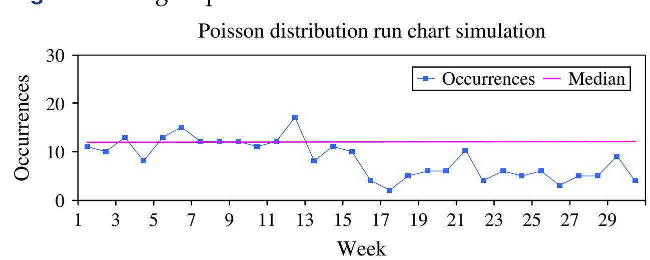
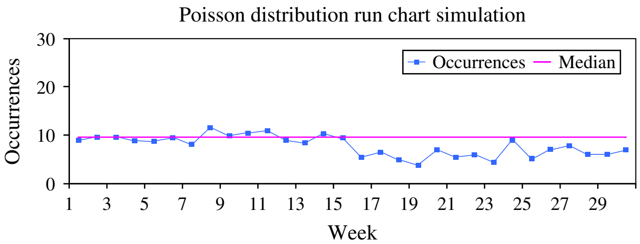


Figure 8. Subgroup Size of 5—Poisson Distribution



and 5 perform rather similarly, thereby offering important guidance on process improvement data collection strategies.

4. Conclusions

We have discussed the design and use of spreadsheet simulation models to illustrate the impact of underlying process variation, anticipated levels of improvement, and subgroup sizes on run chart behavior. We have depicted these models with two particular random variables (Normal and Poisson). The spreadsheet models expose workshop participants and college program students to the use of statistical methodologies in process analysis and improvement by allowing them to be active participants in the topic. Instead of becoming inactive bystanders, this simulation tool permits students to play with different parameter settings and instantly observe the results. Students can perform "what-if" analysis and immediately examine the impact.

Running the model requires no advanced spreadsheet skills. Indeed, participants simply enter specific values, select an appropriate subgroup size (through a shortcut key), and hit "F9" to obtain additional simulation replications. Instructors in more advanced spreadsheet model-building courses could make the creation of this simulation tool one of their course assignments. As currently developed, this spreadsheet model requires no Visual Basic for Applications (VBA) programming; indeed, the most complex parts of the model-building from a student's perspective may be the MAX(NORMINV(RAND( ), *mean*, *standard_deviation*), 0) function to draw non-negative values from the Normal distribution, the calculation of Poisson distribution probabilities, and the resulting simulation of those Poisson-distributed values. True, the pre-selected macros were created using VBA programming but the current spreadsheet simply requires students to use shortcut keys to model various subgroups.

The spreadsheet simulation model helps the instructor articulate data collection and process improvement in a visual environment. It is this "value of visibility" that we feel is the most compelling feature of our inclass exercise. One cannot underestimate the value of a visual tool in conveying analytical concepts.

Although our undergraduate and executive education students appear to enjoy using this spreadsheet tool (as described in the Introduction), we recognize opportunities for further study. For instance, we could determine whether the entertainment and positive impressions provided by this tool result in greater comprehension of statistical principles (Clayton and Sankar 2009). A possible approach to test this tool would be to administer a test or assignment on subgroup size concepts to two groups of our students, one of which played with the simulation model while the other received typical lecture coverage. One may also be able to test this with a single group of students by conducting a subgroup size test before and after presentation of the simulation model.

In addition, we could insert a slider in the spreadsheet so that students or workshop participants could change the subgroup size to any desired quantity. This modification would permit one to visually explore the outcomes from any subgroup, rather than the preselected options included with the current model.

Endnote

[1] The spreadsheet tool is provided as supplemental files to this paper at http://dx.doi.org/10.1287/ited.2016.0160 (Normal run chart simulation.xls; Poisson run chart simulation.xls).

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