Design and Evaluation of SOCR Tools for Simulation in Undergraduate Probability and Statistics Courses

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Abstract

Technology-based instruction represents a new recent pedagogical paradigm that is rooted in the realization that new generations are much more comfortable with, and excited about, new technologies. The free and Internet-based NSF-funded Statistics Online Computational Resource (www.SOCR.ucla.edu) provides a number of educational materials and interactive tools for enhancing instruction in various undergraduate and graduate courses in probability and statistics using observed or computer generated data. SOCR includes class notes, practice activities, statistical calculators, interactive graphical user interfaces, computational and simulation applets, tools for data analysis and visualization. Based on the promising results from our pilot study in 2005-2006, where we saw a consistent trend of improvement in the SOCR treatment group compared to the control group, in terms of quantitative examination measures, our 2006-2007 study involves over 300 UCLA students. We use a cross-over design for one course, (introduction to probability) taught by one instructor, and a randomized controlled study for two different courses (an introductory statistics course for the life sciences and an introductory course in probability). For the cross-over design course, SOCR-based and non SOCR-based activities or homework are assigned and analyzed relative to their performance. In the controlled study, one class uses SOCR the other does not. Several components of the SOCR-based materials are heavily dependent on simulated data to enhance the understanding on distributions, which is a major topic for the classes tested. Little is known about how interactive simulation based applets can enhance students' learning, understanding and interest in statistics. As a result, separate questionnaires (Felder-Soloman Learning Style inventory, ATS survey, and entry and exit assessment of student knowledge questionnaire) are also collected separately to explore how SOCR affects the performance of students in relation to their learning style, attitudes towards statistics, prior knowledge and demographic characteristics, and reaction to these applets. The first goal of this study is to try to associate the effects of SOCR with students' individual learning style based on the Felder-Silverman-Soloman index. How these applets assist students with different learning styles is yet to be observed. Our second goal is to assess students' achievement with a closer look based on homework and activities directly related to SOCR. The students' feedbacks and performances from this study tell us how to best optimize the SOCR resources based on their needs. Moreover, its result gives us a more accurate assessment of SOCR specifically and an assessment of internet-based resources in introductory and more advanced courses of statistics and probability.

Keywords: Education research, simulation applets, teaching with technology, Java applets, online course materials, probability and statistics, SOCR.

1. Introduction

One of the last TIME magazine issues in 2006 (Wallis et al.) described schools as not keeping up with the pace of the outside world and that advances in technology has not influenced the classroom at the level that it should have been. Even though the TIME magazine article refers to secondary schools, the same things may be said about traditional methods of teaching in colleges and universities. The push for a technology-enriched curriculum with real world applications is the exact same driving force that demands more simulations and computer-based activities in the classroom. Simulation helps students learn concepts through different scenarios with controlled parameters. The aims of new activities and curricula involving information technology and simulations are not just to help instructors present new concepts, but also to improve students' conceptual understanding and provide realistic and practical examples that parallel theoretical modeling. The positive effect of simulation-based instruction was supported by experiments with university students, (Garfield and del Mas, 1989, 1994) where it was found that students can understand difficult concepts using simulations. However, there are also findings that simulations can add to the formation of misconceptions about statistical concepts (Well et al.,1990; Hodgson,1996).

The objective of this paper is to test the effectiveness of the use of several simulation-based activities in a number of undergraduate introductory statistics and probability courses. The use of simulations and technology-based instruction is not new, (Mills, 2002; Hodgson, 2000; Puranen, 2005); however little is known about the effect of simulations in relation to the students' learning styles. To address this void, we study the associations between students' learning styles, based on the Felder-Soloman Index, the use of simulation-based activities through the Statistics Online Computational Resource (SOCR) and quantitative performance.

2. The Statistics Online Computational Resource (SOCR)

The core SOCR is composed of four major components: computational libraries, interactive applets, hands-on activities and instructional plans. External programs typically use the SOCR libraries for statistical computing (Dinov, 2006a). The interactive SOCR applets are further subdivided into six suites of tools: Distributions, Experiments, Analyses, Games, Modeler and Charts. Dynamic Wiki pages (SOCRWiki, 2006) form the hands-on activities and include a variety of specific instances of demonstrations of the SOCR applets. The SOCR instructional plans are collections composed of lecture notes, documentations, tutorials and guidelines about statistics education. The goals of SOCR are to design, validate and freely disseminate knowledge. SOCR specifically provides portable online aids for probability and statistics education, technology based instruction and statistical computing. SOCR tools and resources include a repository of interactive applets, computational and graphing tools, instructional and course materials. SOCR efforts are focused on producing new and expanding existent Java applets, web-based course materials and interactive aids for technology enhanced instruction and statistical computing (Dinov 2006b; Leslie, 2003). Many SOCR resources are useful for instructors, students and researchers.

3. Purpose of the study - Evidence

The purpose of this study is to examine the impact of simulation using interactive applets tools on students' performance in relation to their learning styles, and to validate the effectiveness of SOCR. A first attempt on the effectiveness of SOCR was performed during the Academic Year 2005-2006 where promising results were found for the classes that used SOCR compared to those that did not, (Dinov et. al., 2006). This was shown in the test results where the classes that used SOCR consistently outperformed those that did not, but also in the end-of-the-quarter surveys where the students indicated satisfaction in using the various tools of SOCR. For our study we have administered a beginning- and end-of-the-course attitude surveys on statistics and probability as well as a satisfaction survey at the end of the course. An important element of the study is the Felder-Silverman-Soloman Index of Learning Styles (ILS) (Felder and Silverman, 1988; Felder, 1998), which is a self-scoring instrument that assesses student learning preferences on a four dimensional scale – Sensing/Intuiting, Visual/Verbal, Active/Reflective and Sequential/Global. There are web-based and paper versions of the ILS, go to which may be utilized in various types of courses (http://www.ncsu.edu/felder-public/ILSpage.html).

The ILS index is based on a model of learning, where students' learning styles are defined by their answers to five classes of questions: 1) Type of preferential information perception: sensory (sights, sounds, physical sensations), or intuitive (possibilities, insights, hunches). 2) Preferred external information sensory channel: visual (pictures, diagrams, graphs, demonstrations), or auditory (words, sounds). 3) Information organization: inductive (principles are inferred based on facts and observations), or deductive (principles are given and applications are deduced). 4) Information processing: active (through engagement in physical activity and discussion), or reflective (through self-examination). 5) Understanding process: sequential (continual steps), or global (generative/holistic approach). The ILS allows instructors who assess the behavior of each class, adapt their teaching style to cover as much of the spectrum on each of the four dimensional axes as possible. Of course, this requires a commitment of time, resources and willingness to modify course curricula. If the ILS assessment is appropriately utilizes in class, it is reasonable to assume that the instructional process is generally as optimal as possible – i.e., the learning environment is enriched and stimulating for most students in the class (Felder and Silverman, 1988).

4. Design of the Study

In our study, we have included three "Introduction to Probability" classes and two introductory statistics classes with more than 300 students participating. Different design was used for each of the three courses. One instructor used a crossover design to compare the outcomes on SOCR-based instruction and non-SOCR-based instruction for two probability classes, while the other two instructors compared their SOCR-treatment classes against identical control courses from Fall 2006 that did not employ SOCR.

4.1 Description of Statistics 13

Statistical Methods for the Life and Health Sciences (UCLA Stats 13) is an introductory course on statistical methods for the life and health sciences. Most enrolled students are bound for medical, graduate and professional schools after completing their undergraduate curricula. Brief outline of the course is available online at http://www.registrar.ucla.edu/Catalog/catalog05-07-7-98.htm and the section-specific information is listed below. Each of the two sections taught for this study received 5 hours of instruction a week – 3 lectures, one discussion and one laboratory. For discussion and laboratory, each section was split into three sub-sections, which were conducted by teaching assistants. There were two distinct teaching assistants for each section. All students were assessed using the same gradebook schema and grade distribution. SOCR tools were used in lecture for demonstration, motivation and data analysis, as well as for project, lab, and homework assignments..

4.2 Description of Statistics 100A

Introduction to Probability Theory (UCLA Stats 100A, Fall) is the first course in a three-course sequence. The other two are Introduction to Mathematical Statistics (Winter) and Regression Analysis (Spring). Most enrolled students are from Mathematics, Economics, and Computer Science majors. A description of the course can be found at http://www.registrar.ucla.edu/Catalog/catalog05-07-7-94.htm. The class meets 3 times a week with the instructor and once a week for a discussion with a teaching assistant. In the Fall 2006 quarter there were 3 lectures of Statistics 100A.

5. Sample Activities

Below we will discuss three activities that we have used in our classes using simulation-based SOCR applets. We should mention here that the interested reader may find a complete list of activities and educational material at http://wiki.stat.ucla.edu/socr/index.php/SOCR_EduMaterials and http://www.socr.ucla.edu.

a. The Die Coin Experiment:

This experiment can be accessed at http://www.socr.ucla.edu/htmls/SOCR_Experiments.html. A fair die is rolled and the number observed X is recorded. Then a fair coin is tossed X number of times. For example, if the die outcome is X=2 then the coin is tossed twice, etc. Let Y be the number of heads observed. We can use this activity to enhance the teaching of discrete joint probability distributions by first constructing the joint probability distribution of X and Y and then finding the marginal distribution of Y. In **Figure 1** we can see a snapshot from SOCR of the marginal distribution of Y. In this snapshot we observe, in blue, the theoretical distribution of Y, with the theoretical mean and standard deviation, while the shaded area represents the empirical distribution of Y when the experiment is run 1,000 times. In the snapshot we can also observe the theoretical and empirical mean and standard deviation. The user can choose to run the experiment once, few times, or many times and be able to observe the closeness of the empirical to the theoretical distribution as the number of runs increases. The distribution of the die score can be chosen by the user (e.g., $P(X=i)={}^{1}/_{6}$ for i=1,…,6, if fair die), and so can the probability of heads (e.g., p=0.5, for a fair coin).

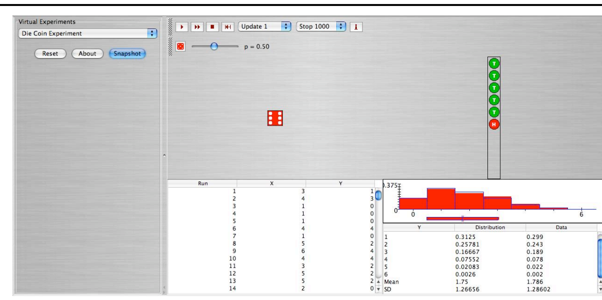

Figure 1: A snapshot from SOCR of the result of 1,000 runs of the Die Coin Experiment.

b. Central Limit Theorem (CLT):

This applet provides the capability of sampling from any of the more than 40 SOCR distributions, as well as from a customize distribution that can be contiguous and discontinuous, symmetric and asymmetric, unimodal and multi-modal, leptokurtic and mesokurtic and other types of distributions. For a complete description the interested reader can visit http://wiki.stat.ucla.edu/socr/index.php/SOCR_EduMaterials_Activities_GeneralCentralLimitTheorem. Once the distribution is chosen the user can examine the distribution of the sample mean, median, sample variance, and other statistics. **Figure 2** below gives a better idea of this SOCR tool.

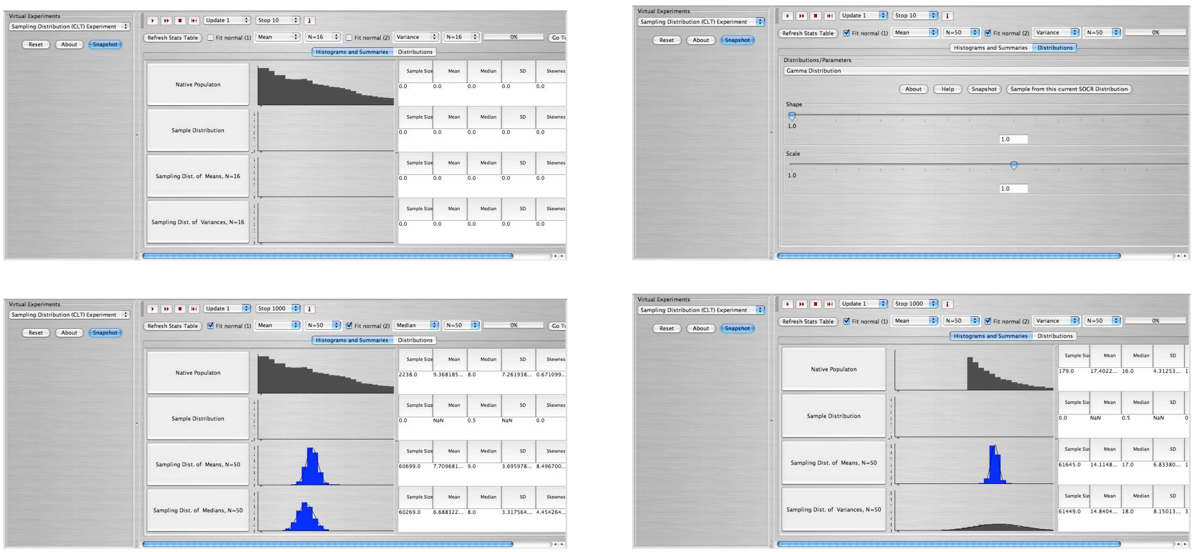

Figure 2: Four SOCR snapshots of the Central Limit Theorem Applet.

c. Application of the Central Limit Theorem:

It is believed that life-times, in hours, of light-bulbs are Exponentially distributed, say $Exp\left(\lambda = \frac{1}{2{,}000}\right)$, mean expected life of 2,000 hours. Recall that the Exponential distribution is called the *Mean-Time-To-Failure* distribution. You can find more about it from the SOCR Distributions applet. Suppose a University wants to purchase 100 of these light-bulbs and estimate the average life-span of these light bulbs. What is a CLT-based estimate of the probability that the average life-span exceeds 2,200 hrs? $X_i \sim Exp\left(\lambda = \frac{1}{2{,}000}\right)$ and $\overline{X} = \frac{1}{100}\sum_{i=1}^{100} X_i$. Notice that in this case the exact distribution of $\overline{X}$ is (generally) not Exponential, even though the density may be computed in closed form (Khuong & Kong, 2006). If we use the CLT, however, we can approximate the probability of interest

$$P(\overline{X} > 2{,}200) \cong P\left(\overline{X} > 2{,}200 \middle| \overline{X} \sim N\left(\mu_{\overline{X}} = 2{,}000,\ \sigma^2_{\overline{X}} = \frac{(2{,}000)^2}{100}\right)\right),$$

as we know that the mean and the standard deviation of X_i are $\frac{1}{\lambda} = 2{,}000$ and the standard deviation of $\overline{X}$ is $\frac{1}{\lambda\sqrt{100}} = 200$. Therefore, P($\overline{X}$ >2,200) ~ 0.158655, using the CLT approximation and the SOCR Distributions calculator, **Figure 3**.

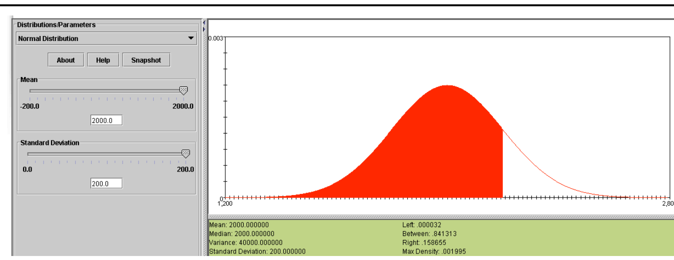

Figure 3: A snapshot from SOCR calculating the probability.

d. Law of Large Numbers (LLN) Simulation Activity:

The probability of winning a certain game is p. We want to examine the long-run behavior of the proportion of wins. This can be done through the Coin Toss SOCR LLN activity (http://wiki.stat.ucla.edu/socr/index.php/SOCR_EduMaterials_Activities_LawOfLargeNumbers). Let us choose $n=1,000$ and $p=0.40$. In this LLN experiment we observe in **Figure 4** the convergence to the true $p=0.40$ when the number of experiments increases. One misconception of the LLN is that the number of heads should be equal to the number of tails if we toss a fair coin many times. As we observe from the graph this is not true (actually the difference between wins and losses diverges) but the probability of win converges to the true probability as it was previously mentioned. For example when $n=200$, and $p=0.40$ we may see 85 wins ($\hat{p}=0.425$ and difference between wins and losses is $115-85=30$) while when $n=100$ we may observe 38 wins ($\hat{p}=0.38$ and difference between wins and losses now only $62-38=24$). In this example, we see that even though the difference between wins and losses increases the sample proportion is closer to the population proportion as n gets larger. We should mention here that we report the normalized differences of the number of Heads minus the number of Tails in the graph and the result table. Let H and T are the number of Heads and Tails, up to the current trial, respectively. Then $|H-T|$ is normalized so that the expectation $E(|H-T|) = p$, using the fact that $E((1-p)H-pT) = 0$. This ensures that the normalized differences oscillate around the chosen p and they are visible within the graph window.

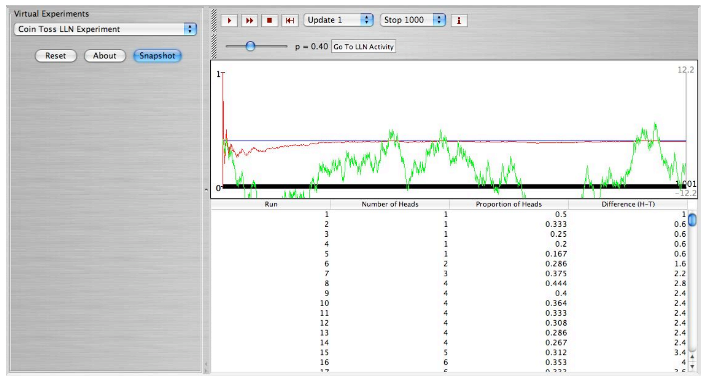

Figure 4: A snapshot from SOCR showing the result of 1,000 tosses of coin with probability of heads p=0.40.

6. Results

A comparison between the final scores for the classes that used SOCR against the control classes (No SOCR usage: Fall 2006: Stat 13 - Dinov and Christou and Stats 100A – Christou against Fall 2005/Winter 2006: Stats 13 - Dinov, Stats 100A – Christou, Stats 13 - Christou) using two sample t-tests shows encouraging results. These courses had the same grading style (exams and homework) and therefore they are comparable. The results from one pair of control (Fall 2005 Stats 100A) and treatment (Fall 2006 100A) classes by Christou are presented in **Table 1**. These show that there is significant difference at 5% in the means for exams 3, 4, and 5 as

Table 1: Quantitative Results measuring student learning in the two Stats 100A classes (Christou, Fall 2005, Fall 2006).

	Group	High	Low	Median	Mean	Standard Deviation	Statistics
Exam 1	**Control**	96	33	68	69.97	18.52	$t_o = 0.99$ $t(71)$ $p=0.17$
	Treatment	97	33	60	65.74	18.05	
Exam 2	**Control**	100	40	88	83.85	14.93	$t_o = 0.81$ $t(71)$ $p=0.21$
	Treatment	100	41	86	81.10	14.12	
Exam 3	**Control**	100	32	71	71.12	16.75	$t_o=-3.87$ $t(71)$ $p=0.0001$
	Treatment	100	58	87	83.64	10.58	
Exam 4	**Control**	100	36	79	78.35	16.56	$t_o=-3.20$ $t(71)$ $p= 0.001$
	Treatment	100	65	90	88.05	8.61	
Exam 5	**Control**	100	40	81	80.38	15.17	$t_o=-2.46$ $t(71)$ $p=0.008$
	Treatment	100	66	89	87.44	8.90	
Overall Performance	**Control**	94.31	44.93	78.14	78.36	12.87	$t_o=-2.16$ $t(71)$ $p=0.017$
	Treatment	98.77	66.59	85.92	83.69	7.91	

well as the overall performance (34 students in the control group, 39 students in the treatment group). Also, the variation in the SOCR treatment section (Stats 100A) is smaller, which shows a consistent overall improvement. We should mention here that these results agree with our findings in the previous smaller scale pilot preliminary testing during the Fall 2005 quarter (Dinov, 2006). As for Stat 13 (Christou), **Table 2** shows mixed results but the overall performance is again in favor of the SOCR-based instruction. These mixed results may be accounted for by the fact that Statistics 13 has a required lab hour for the non SOCR-based instruction class as well. This lab hour exposed the students to the statistical software Stata, which means that the students had some exposure to technology-based instruction. The results from Dinov's Stats 13 classes are shown in **Table 3**.

Table 2: Quantitative Results measuring student learning in the two Stats 13 classes (Christou, Winter 2006, Fall 2006).

	Group	High	Low	Median	Mean	Standard Deviation	Statistics
Exam 1	**Control**	100	44	83	81.41	14.05	t_o = -0.63 t(165) p=0.27
	Treatment	100	46	84	82.68	11.92	
Exam 2	**Control**	100	6	81	76.75	18.25	t_o = -5.92 t(165) p<0.001
	Treatment	100	35	95	90.86	12.19	
Exam 3	**Control**	100	35	85	81.61	14.58	t_o=-0.37 t(165) p=0.36
	Treatment	100	50	84	82.36	11.62	
Exam 4	**Control**	100	37	86	83.94	10.70	t_o=1.63 t(165) p= 0.06
	Treatment	100	54	83	81.07	11.96	
Exam 5	**Control**	100	20	79	78.75	13.84	t_o=-4.84 t(165) p<0.001
	Treatment	100	50	91	87.80	10.02	
Overall Performance	**Control**	94.31	43.91	85.42	82.09	11.6	t_o=-3.07 t(165) p=0.001
	Treatment	97.49	69.17	88.68	86.67	7.37	

The design for the Stats 100A class (sections 3 & 4) of Juana Sanchez was different. At the beginning of the quarter, all topics to be covered were randomly numbered and then each topics to be covered in Section 3 was assigned a SOCR or Traditional treatment. The numbers of SOCR and Traditional treatment topics were the same. Then the topics covered in Section 4 were assigned the opposite SOCR and Traditional treatments as in Section 3. **Table 4** shows that for one class, the performance was much better in questions using SOCR

Similarly, we can compare the SOCR questions performance in one group with the performance on the same questions for the group that did not use SOCR for those questions (not shown here). We did not find (in this last analysis) significant results without controlling for the differences between the two groups, which is not unreasonable since one class had mostly graduate students (section 3) and the other mostly undergraduates. The results we are showing above in **Table 4** are based on a *t*-test for paired data and the *p* values are for the one-sided hypothesis that the treatment group performed better than the control group. Control group in each class means performance for the questions on topics not learned with SOCR. The treatment group refers to performance in questions that were learned with SOCR. So what we compare in each section is whether students performed better in the final exam in those questions that they learned using SOCR.

Table 4: Quantitative results measuring student learning in the two Stats 100A classes (Sanchez, Fall 2006), final exam.

	Group	High	Low	Median	Mean	Standard Deviation	Statistics
Section 3	**Control**	100	17.69	80.76	76.26	17.47	t_o = 1.70 t(54) p=0.047
	Treatment	100	48	89	83.76	15.451	
Section 4	**Control**	100	42	90	80.32	17.78	t_o = -1.50 t(64) p<0.9318
	Treatment	100	26.9	80.76	73.56	18.6	

We present now the results of the Index of Learning Styles (ILS) and its impact on students' learning for one of the courses that participated in the study (Statistical Methods for the Life and Health Sciences – Statistics 13 – Christou). At the beginning of the course each student completed the online ILS questionnaire consisting of 44 questions. Based on the answers they provide they receive a score from –11 to 11 for each one of the four categories. The four categories are: S1: Active-reflective (a score closer to +11 indicates that the student is more reflective than active); S2: Sensing-intuitive; S3: Visual-verbal; and S4: Global-sequential. We try to explain the overall students' performance with some independent variables (the four categories S1, S2, S3, S4, and students' attitudes towards statistics and probability). Students' attitudes (post) were determined by a survey that each student completed at the beginning and the end of the course. The regression results are shown on **Table 5** below.

The variables that were significant predictors of overall performance, at the 5% level, included the active-reflective and visual-verbal ILS measures and the attitude towards the discipline. The fact that the global-sequential and sensing-intuitive directions of the ILS spectrum did not play a significant role in explaining overall student performance makes the interpretation of the ILS results difficult. One possibility for explaining this observed effect is that an increase of the overall student performance positively and directly correlates with both – a shift of the learners into the *active (*tendency to retain and understand information by doing or applying something active) and *verbal* (written or spoken word explanations) spectra of the ILS space.

Table 5: Regression results for the ILS effects on overall quantitative performance for the Stats 13 (Christou).

Source	SS	df	MS
Model	956.969029	3	318.989676
Residual	4070.82122	68	59.865018
Total	5027.79025	71	70.8139472

Number of obs	= 72
F(3, 68)	= 5.33
Prob > F	= 0.0023
R-squared	= 0.1903
Adj R-squared	= 0.1546
Root MSE	= 7.7372

tot	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
S1	-.5947788	.2680462	-2.22	0.030	-1.129657	-.0599009
S3	.7596321	.2883656	2.63	0.010	.1842076	1.335057
post	.504371	.2254381	2.24	0.029	.0545162	.9542258
_cons	67.50669	8.583663	7.86	0.000	50.37826	84.63512

7. Conclusion

Our study demonstrates that simulations may be powerful instructional tools that complement classical pedagogical approaches for explaining difficult statistical concepts in probability and statistics classes. This is enforced from the fact that utilizing visualization, graphical and computational simulation tools in teaching provide valuable complementary means of presenting a concept, property or an abstract idea. In addition, such IT-based pedagogical instruments are appreciated and well received by our students who normally operate in technological environments far exceeding these of their instructors. In our experiments, we saw effects of using SOCR simulation tools even when we did not completely stratify the student populations and did control for all possible predictors (like age, major, learning style, background, attitude towards the subject, etc.) The effects we saw within each class are weak cues favoring the blended instruction. However, pooling these results across classes demonstrated a statistically significant effect of the IT-based teaching approach. Furthermore our study shows that the students' learning style can be an important factor on their performance, however we do not mean in any way that we should use simulations only for one or the other learning style group.

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