

Comparing traditional versus alternative sequencing of instruction when using simulation modeling

Introduction

Through the traditional method of the learning process, students are first exposed to the content by the classroom teacher. In an engineering context, concepts are learned and students have the opportunity to gain an understanding of the theoretical background and purpose of the theories. During this process, the classroom teacher may show classic examples of where the theory may be applied. The students may have the opportunity to demonstrate knowledge of the content through formative or summative assessments. In technology education classrooms, the students typically develop a project or artifact to demonstrate their understanding of the material to solve a problem presented by the teacher (Mentzer, 2011). As part of this process, students may have the opportunity to use simulation modeling. Computer simulation modeling is an engineering tool used to solve problems. Computer Simulation was defined by de Jong and van Joolingen (1998) as "a program that contains a model of a system (natural or artificial) or a process". Simulations allow users to examine resulting values of computations after establishing the parameters of the system (Smith & Pollard, 1986). The parameters can then be adjusted, based on the results, and further computations can be analyzed. Simulation has traditionally been used as a tool or resource to apply the content knowledge learned. Once the theoretical knowledge is learned, simulation modeling is introduced as a tool to demonstrate the application of the learned theory. By using simulations, students can test a greater number of models and run multiple iterations of testing before committing to a final solution. This provides an efficient method of knowledge application because students can learn how the theory is used in multiple situations and can gain knowledge about the authentic application of course content. Engineering concepts

can be introduced to the students, and then simulation modeling can be integrated in order for students to apply the learned knowledge.

Simulation modeling can be extremely beneficial in expanding student learning when used in combination with physical models to illustrate engineering and design concepts (Clark & Ernst, 2006; Ernst & Clark, 2009; Jaakkola, Nurmi, & Veermans, 2011; Newhagen, 1996; Smith & Pollard, 1986; Zacharia, 2007). This can be especially useful in a project-based curriculum typically found in technology education. For example, bridge building and CO₂ cars are two popular middle grade activities. However, both of these activities require consumable materials and substantial time to complete physical models. It would be extremely difficult for a classroom teacher to spend the time necessary for students to participate in the testing, evaluation, and redesign steps of the engineering design process using only physical models as the artifact. By incorporating simulation modeling into the lesson, students can create multiple virtual models, as well as test and redesign them as necessary (Deal, 2002; Piccoli, Ahmad & Ives, 2001). These simulations allow the student to experience all the steps of the engineering design process and complete the learning loop for testing and redesign. Once a student has created a final optimized solution, a physical model can then be built tested.

There has been a significant amount of research on simulation modeling. In 2012, Rutten, van Joolingen, and van der Venn published research summarizing how computer simulation has been used in science education during the previous decade. Their results show that simulations play a significant role in the science education system at the post-secondary level, and results vary among their ability to increase achievement. Although there is much research about simulation modeling, there is little research on how simulation model is being incorporated at the secondary

level. There is also little research demonstrating the effects of sequencing computer simulation with traditional content knowledge in order to increase the opportunity for student learning in a technology and engineering education classroom. The traditional method of teaching is to deliver the content knowledge of the lesson and then give the students an opportunity to demonstrate their understanding of the concepts through physical modeling. The teacher may or may not offer formative assessments during the lesson or may require a summative assessment between the content and physical model or at the end of the project. However, the current research project suggests the traditional sequence of content delivery with building the physical model may not offer the best sequence to increase student achievement and performance. Some research exists showing the sequence of incorporating the learning activities may have an impact on student learning (Clarke, Ayres, & Sweller, 2005). However, there is very little research on this topic in the context of technology education. The researchers have designed the methodology of this research project to determine if an alternative sequence of virtual modeling and content delivery has an effect on student achievement and performance within a technology education classroom. Therefore the research questions for this study are:

1. Does the sequencing of content knowledge and simulation modeling have an effect on the students' content knowledge achievement?
2. Does the sequencing of content knowledge and simulation modeling have an effect on the students' performance as measured by bridge design efficiency?
3. Does the sequencing of content knowledge and simulation modeling have an effect on the students' engagement in learning STEM content?

Methodology

The concept of this research project is to measure if a significant difference exists in various aspects of content knowledge and bridge design depending on the sequence in which the material and virtual modeling are presented to the student. Therefore, students in separate groups were exposed to structures content and virtual bridge design in a different sequence. The following sections describe the methodology of the research project, how the sequence of instruction was administered, and how the modeling program was used to collect data.

Research Participants

The students participating in this study are 8th grade students in an upper-midwestern middle school. At this school, all the students are required to take one quarter, or nine weeks, of a technology education course. Therefore, the classroom teacher implementing the simulation program in the classroom has a new student roster each quarter. The project involved four classes throughout the day and was administered during two quarters. These four classes were divided into two groups, a control group and experimental group, with two classes each quarter being in each group. All the students in these classes were of mixed ability and there is no intentional grouping of these students by the school. However, due to the educational setting and various aspects that determine student scheduling, this study is classified as quasi-experimental and assumes non-parametric conditions. The classes chosen to be in the control and experimental groups were chosen at random among the courses available.

Control and Experimental Group

Both the control and experimental groups took a pre-test at the beginning of the study. The difference between the control and experimental groups was the sequence in which the material

and virtual content were delivered. After the pre-test, all the students in both groups were given login information for the Whitebox Learning Structures 2.0 platform. A description of the platform is provided in the next section. The control group proceeded through research, content, and modeling applications in the sequence just as the program is designed. This includes reading background information, learning about the details of bridge design while completing built-in formative assessments, and modeling and testing truss designs. The experimental group began the structures application by initially skipping the research, content, and formative assessments and began working directly with the tutorial to design the truss. Each student in this group was given a hard copy of the bridge building tutorial. This is due to the structures content being embedded within the virtual tutorial because of the STEM-based approach to the modeling program. The researchers needed to eliminate the possibility of students gaining built-in content delivery before finishing the design of their virtual models. Therefore, a hard copy of the tutorial was provided so the students could design their virtual models without being exposed to the embedded structures content. Once the students in the experimental group had a completed truss design and tested their virtual models, they went back to the research portion of the application and proceeded through the content and formative assessments. Once both groups finished the content and virtual models, the truss templates were printed and the physical models were constructed. Once all of the physical models were tested, the students in both groups took the post-test. A summary of the sequencing of activities for each group is shown in Fig. 1.

Control: Pre-test > Content > Virtual Modeling and Testing > Physical Model > Post-test

Experimental: Pre-test > Virtual Modeling and Testing > Content > Physical Model > Post-test

Figure 1. Sequencing for Control and Experimental Groups

Structures Virtual Platform

Although there are many virtual and computer simulation bridge building software programs available, this research project used the virtual modeling program Structures 2.0 published by Whitebox Learning. Whitebox Learning is a web-based platform that has multiple applications for STEM-based instruction and has several different types of virtual modeling components. For this project, the researchers used Structures 2.0, which is a bridge building design and simulation program focused on integrating content of bridge design with the application of virtual modeling. The program begins with an introduction of structures and gives students some background knowledge. This section provides basic engineering concepts such as truss components, factors of safety, and other definitions related to general structure design. The next phase of the program provides a research section, allowing students the opportunity to gain an in-depth knowledge of truss design. The application gives a step-by-step lesson on how to design trusses and how to determine what makes an effective truss design. Formative assessments are built into the research section in order for students and the teacher to measure their understanding of the material. This instructional software addresses 17 of the 20 standards specified in the Standards for Technological Literacy (2007) and engineering practices specified in the Next Generation Science Standards (2014). It is important to note that the readings provide the context of the problem and address engineering design standards as well as the technical knowledge that applies to designing an efficient bridge. Once the students complete the research section, a detailed tutorial shows the students how to use the functions necessary to design a virtual model of a bridge. During the virtual design process, students can design different varieties of trusses. As the students design trusses, they can test them to see how much weight the truss can support before failure. Each time a student tests a truss design, the program records an iteration. These

iterations can be within specifications or out of specifications based on the particular requirements predetermined by the teacher and setup in the teacher control center. However, the program will only logs efficiencies for in-spec iterations. Once the student has finalized a truss design, the program will print out the template of their truss so the student will have a template to build a physical model. The students build two identical trusses that are joined together to make a bridge. Once the physical model is complete, the student tests the physical model to measure the efficiency of the bridge.

Data Collection and Analysis

While the students are navigating through the structures application, the researchers can monitor the students' activity and progress through the teacher control center. The teacher control center measures different aspects of the students' progress. In this research study, the virtual simulation data collected from the Structures 2.0 application is shown below.

Item	Measured
Efficiency of the first virtual model	total weight held divided by weight of the bridge
Efficiency of the best virtual model	total weight held divided by weight of the bridge
Class Progress	# activities visited within research section of the program (17 possible)
Class Grades	average grade of completed formative assessments within research section of the program
Time on Task	# minutes spent within research section of the program

In-Spec Iterations	# of tests for each design within specifications
Out-of-Spec Iterations	# of tests for each design out of specifications
Total Iterations	# tests for in-spec and out-of-spec iterations combined

The purpose of collecting this data was to approach the research questions from different aspects in order to draw a conclusion as to how the students' knowledge, performance, and engagement were affected by the different sequencing of activities. The primary statistical analysis compared the pre/post test results and the virtual model bridge efficiencies. Engagement was measured by formative evaluation which included class progress, formative quiz grades and time on task reports.

In addition to the virtual data, the efficiency of the physical model was also collected to measure engineered performance. The students also took a traditional pre and post test to determine student achievement of content knowledge. The pre and post tests consisted of 15 multiple choice items to measure the students' understanding of the content in the Structures 2.0 platform. The items for these tests were developed by the researchers based on the content covered through the research portion of the Structures 2.0 application and reviewed by experts to ensure content validity. Once collected, the data was statistically analyzed using the Wilcoxon Scores (Rank Sums) two-sample test. This test was used due to the quasi-experimental design where non-parametric conditions were applied.

Results

The statistical results for the pre and post test scores are shown in Table 1.

Table 1

Statistical analysis for difference in means of test scores

<u>Concept</u>	<u>N</u>	<u>Min.</u>	<u>Max.</u>	<u>Sum of Scores</u>	<u>Mean Score</u>	<u>Z</u>	<u>P-Value</u>
Pre-test							
Control	39	4	15	1778	45.6	0.53	0.600
Experimental	48	3	15	2051	42.7		
Post-test							
Control	39	6	15	1837	47.1	1.23	0.221
Experimental	47	6	14	1904	40.5		
Difference (Post minus Pre)							
Control	39	-5	8	1736	44.5	0.34	0.734
Experimental	47	-5	6	2005	42.7		

The data shows the control group had higher a mean score on the pre-test, post-test, and the difference between the pre and post-test, although not at the significant level. Of these three, the researchers are primarily analyzing the difference in the gain between the pre and post-test.

According to the statistical analysis there was not a significant difference in the gain in mean of the test scores between the control and experimental groups ($p = .734$).

The statistical results for the virtual and physical model efficiencies, as well as the iteration data, are shown in Tables 2 and 3, respectively.

Table 2

Statistical analysis for virtual and physical model efficiencies

<u>Concept</u>	<u>N</u>	<u>Min.</u>	<u>Max.</u>	<u>Sum of Scores</u>	<u>Mean Score</u>	<u>Z</u>	<u>P-Value</u>
First Virtual Model Efficiency							
Control	35	834	5030	1385	39.6	0.39	0.700
Experimental	41	768	4520	1541	37.6		
Best Virtual Model Efficiency							
Control	35	834	11440	1204	34.4	-1.49	0.136
Experimental	41	1280	14400	1722	42.0		
Difference in Virtual Model Efficiencies (Best minus First)							
Control	35	0	6410	1160	33.1	-1.98	0.048*
Experimental	41	0	9920	1767	43.1		
Difference in Virtual Model Efficiencies (Best minus First; without students with only one in-spec iteration)							
Control	34	0	6410	974	28.6	-2.75	0.006*
Experimental	36	0	9920	1511	42.0		
Physical Model Efficiency							
Control	37	72	1402.1	1554	36.4	-1.91	0.056
Experimental	46	56	1377	1932	46.5		

* significant at $\alpha = .05$

Table 3

Statistical analysis for virtual model iterations

<u>Concept</u>	<u>N</u>	<u>Min.</u>	<u>Max.</u>	<u>Sum of Scores</u>	<u>Mean Score</u>	<u>Z</u>	<u>P-Value</u>
In-Spec Iterations							
Control	37	0	45	1570	42.4	-0.02	0.986
Experimental	47	0	80	2000	42.6		
Out-of-Spec Iterations							
Control	36	0	35	1534	42.6	0.20	0.843
Experimental	47	0	50	1952	41.5		
Total Iterations							
Control	39	0	64	1649	42.3	-0.57	0.570
Experimental	48	0	114	2179	45.4		

The results show the control group achieved a higher mean score for the first virtual model, although not significantly. The experimental group achieved higher efficiencies for both the best virtual model and the physical model efficiency, although not at the significant level. The experimental group achieved significantly higher efficiencies in both and the difference between the best and first virtual efficiency ($p = .048$) and the difference between the best and first virtual model without the students with only one iteration ($p = .006$). The analysis was conducted without the students with only one in-spec iteration because their difference between the best and first efficiency would automatically be zero, since the first and best model would be the same. The researchers wanted to analyze the differences in best and first iterations for students that conducted more than one iteration, which would be a better indication of iterative design through application of the complete design process. The results show there is no significant difference between the control and experimental groups in regards to in-spec iterations, out-of-spec iterations, and total iterations. The statistical results for class progress, class grades, and time on task are shown in Table 4.

Table 4

Statistical analysis for class progress, class grades, and time on task

<u>Concept</u>	<u>N</u>	<u>Min.</u>	<u>Max.</u>	<u>Sum of Scores</u>	<u>Mean Score</u>	<u>Z</u>	<u>P-Value</u>
Class Progress							
Control	39	0	17	2118	54.3	3.46	0.001*
Experimental	48	0	17	1710	35.6		
Class Grades							
Control	39	0	100	1917	49.1	1.74	0.082
Experimental	48	0	100	1912	39.8		
Time on Task							
Control	39	0	44	2157	55.3	3.77	< 0.001*
Experimental	48	0	40	1672	34.8		

* significant at $\alpha = .05$

The results show the control group achieved significantly higher values for class progress ($p = .001$) and time on task ($p = < .001$). The mean score for class grades was higher for the control group, although not at the significant level.

Discussion

The purpose of this research project was to determine if the sequencing of content knowledge and simulation modeling made a difference in a student's gain in content knowledge, their ability to construct efficient virtual and physical models of bridges, and learning engagement. The first research question asked if sequencing of content knowledge and simulation modeling have an effect on the students' content knowledge achievement. From the analysis, there was not a significant difference between the two groups in the gain in content knowledge as shown by the results of the pre and post tests.

Traditional sequencing has the student learn the content knowledge before virtual modeling and therefore would logically provide students increased ability to design a more efficient virtual model. The researchers hypothesized that students engaged in the simulation first would result in the content being more meaningful to the student and aid in comprehension and knowledge application, research question 2. Although there was not a significant difference in the first or best virtual design between the groups, there was a significant difference in the difference in the best and first design. This indicates the experimental group was able to significantly improve their design more than the control group while using the simulation program. These results suggest that other factors may be involved when measuring student performance while changing the sequence of instruction. Although the experimental group had a significantly higher average for the difference in the best and first virtual efficiency, there was not a significant difference in

the virtual efficiency of the first iteration. There is also not a significant difference in the number of iterations performed by the two groups. The findings of this study suggest that other factors are involved between the first iteration and the best iteration that resulted in the experimental group having a significantly higher gain in virtual efficiency.

For the third research question regarding student engagement in instructional material, the control group had significantly higher averages in class progress and time on task, but not for class grades. By introducing the control group to the content first, students were significantly more engaged in the STEM content embedded in the Structures 2.0 application as shown by class progress and time on task. However, this did not translate into higher formative assessment grades during the research portion of the program. The significant differences for class progress and time on task led the researchers to conclude the traditional sequence of instruction resulted in higher student engagement. However, as stated before, this did not translate to significantly different results in the gain of the formative assessment or pre and post test scores. This finding suggests that researchers need to investigate the level of cognition measured by the formative assessments and pre and post tests.

If the learning objective is performance as measured by the efficiency of the virtual model bridge, the results of this study show there is value in sequencing the instruction by allowing the students to begin the lesson by first engaging in the simulation modeling as evidenced by the significant difference for the experimental group. However, the theoretical concepts that inform about the development and diffusion of the technology may not be learned as evidenced in the pre-post test results. If the learning objective is knowledge, knowledge application, and engagement, the results show there is value in traditionally sequencing the instruction allowing

students to first encounter the instructional material before moving to the simulation as shown by the significant difference in class progress and time on task, which has been researched as an indicator for student achievement (American Association of School Administrators, 1982; Bowen, 2013; Biderman, Nguyen, & Sebren, 2008; Carroll, 1989; Prater, 1992).

Conclusion

There is little research on how the sequencing of content and simulation modeling on technology and engineering education classrooms affects a student's content knowledge, performance, and engagement. This study was designed to begin looking at how these sequences may affect achievement, engineering design performance, and engagement. Many technology and engineering education teachers integrate simulation modeling in the classroom. Most of these simulations are sequenced after the content delivery in a traditional sequencing format. However, the results of this study show that some variables affecting student performance can be affected by delivering content and simulation modeling in a non-traditional sequence.

Additional research needs to be conducted to look at additional factors of student learning when incorporating simulation modeling into a classroom project. Specifically, the balance of the value of content knowledge and performance must be determined for effective curriculum development, and how the learning outcomes of the project are aligned with state standards, national standards, and standards for technological literacy. Also notable was the difference in variance of the virtual model efficiencies between the control and experimental group. Since non-parametric measures were used, this difference was analyzed using Levene's test, resulting in $F=3.72$ and $P=0.0576$. Although not significant, the large difference in variance of the performance measure may have resulted from students in the experimental group engaging in

trial and error to improve their design rather than knowledge application. Further research is needed to determine when students use either knowledge application or trial and error, or a combination of the two methods. By studying these different aspects, teachers can deliver lessons that include simulation modeling in a more appropriate sequence to increase student knowledge, performance, and engagement in technology and engineering education classrooms.

References

- American Association of School Administrators (1982). *Time on task: Using instructional time more effectively* (No. 81-072808). Publications Fulfillment, Arlington, VA.
- Bowen, B. (2013). Measuring teacher effectiveness when comparing alternatively and traditionally licensed high school technology education teachers in North Carolina. *Journal of Technology Education, 25*(1), 80-98.
- Biderman, M. D., Nguyen, N. T. & Sebren, J. (2008). Time-on-task mediates the conscientiousness-performance relationship. *Personality and Individual Differences, 44*(4).
- Carroll, J. B. (1989). The Carroll model: A 25-year retrospective and prospective view. *Educational Researcher, 18*(1), 26-31.
- Clark, A.C. & Ernst, J.V. (2006). Supporting technology literacy through the integration of engineering, mathematic, scientific, and technological concepts. Published Proceedings of the American Society for Engineering Education Annual Conference and Exposition, Chicago, IL.
- Clarke, T., Ayres, P. & Sweller, J. (2005). The impact of sequencing and prior knowledge on learning mathematics through spreadsheet applications. *Educational technology Research and Development, 53*(3), 15-24.

- de Jong, T. & van Joolingen, W. R. (1998). Scientific discovery learning with computer simulations of conceptual domains. *Review of Educational Research*, 68(2), 179–201.
- Deal III, W. F. (2002). Distance learning: teaching technology online. *Technology Teacher*, 61(6), 21-27.
- Ernst, J. V. & Clark, A. C. (2009). Technology-based content through virtual and physical modeling: a national research study. *Journal of Technology Education*, 20(2), 23-36.
- International Technology Education and Engineering Association (2007, 3rd ed.) Standards for Technological Literacy: Content for the Study of Technology. Reston, VA: International Technology Education and Engineering Association.
- Jaakkola, T., Nurmi, S. & Veermans, K. (2011). A comparison of students' conceptual understanding of electric circuits in simulation only and simulation-laboratory contexts. *Journal of Research in Science Teaching*, (48)1, 71-93.
- Mentzer, N. (2011). High School Engineering and Technology Education Integration through Design Challenges. *Journal of STEM Teacher Education*, 48(2), 103-136.
- Newhagen, J. E. (1996). Why communication researchers should study the internet: a dialogue. *Journal of Communication*, 46(1), 4-13.
- Piccoli, G., Ahmad, R. & Ives, B. (2001). Web-based virtual learning environments: a research framework and a preliminary assessment of effectiveness in basic it skills training. *MIS Quarterly* 25(4), 401-426.
- Prater, M. A. (1992). Increasing time-on-task in the classroom. *Intervention in School and Clinic*, 28(1).
- Rutten, N., van Joolingen, W. R. & van der Venn, J. T. (2012). The learning effects of computer simulations in science education. *Computers and Education*, 58, 136-153.

Science and Engineering Practices (2014). Retrieved July 29, 2014 from
www.nextgenscience.org.

Smith, P. R. & Pollard, D. (1986). The role of computer simulations in engineering education.
Computer Education, 10(3), 335-340.

Zacharia, Z. C. (2007). Comparing and combining real and virtual experimentation: an effort to
enhance students' conceptual understanding of electric circuits. *Journal of Computer
Assisted Learning*, 23(2), 120-132.