How the Introduction of Content Relates to Performance in a Middle School Modeling and Simulation Environment

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Abstract

Modeling and simulation activities are common in secondary technology and engineering education classrooms. Virtual simulations are used to integrate engineering design into classroom instruction. The quality of a student's final virtual design depends on their ability to apply the knowledge they have learned during the lesson. When applying what they learned to the virtual design, a student may reach the limit to which the theoretical knowledge can be applied. At this point, students may resort to other problem-solving processes to improve the design, such as trial and error. The activity in this study is a bridge-building project where the students use virtual modeling software to design a truss. This study measures the performance outcomes of students introduced to the content in different formats to determine how the introduction of knowledge impacts their performance within a virtual simulation. Data was collected through the simulation program and a statistical analysis was used to compare the efficiency of truss designs of students initially introduced to the engineering content to those students not originally introduced to the engineering content. The results of the statistical analysis show that students with more exposure to the content at the beginning of the activity have significantly better performance outcomes in the initial designs. However, students that receive less content initially can perform equally well if given enough opportunities to engage in the simulation activity.

Keywords: Technology Education; Modeling and Simulation; STEM Education; Secondary Education

Introduction

In secondary technology and engineering courses, students typically develop an artifact at the end of a lesson or project to demonstrate their understanding of the content. The purpose of this artifact is to represent the application of the knowledge the student gained when the content is delivered by the classroom teacher (Mentzer, 2011). These artifacts are developed by engaging in the problem-solving process, where students attempt to work through the iterative nature of engineering design. When engaging in the design process, students usually have the opportunity to use a variety of tools in which to demonstrate their knowledge. One of the tools commonly used in a technology and engineering-based classroom is computer simulation (Michael, 2000; Swinson et al., 2016). By using simulation software in the classroom, students create virtual representations of physical objects, analyze designs, and make connections about how various functions are interrelated (Lamoureux, 2009; Piccoli et al., 2001). Simulation activities also allow students to engage in the iterative nature of the design process without the time-consuming aspect of building multiple physical models (de Jong & Joolingen, 1998; Jaakkola et al., 2011; Smith & Pollard, 1986). Existing research demonstrates that gains in learning outcomes may occur within certain simulation-related learning activities when proper scaffolding effectively integrates content with the simulation activity (Basu et al., 2016; Jacobson, Taylor, et al., 2013). Virtual learning environments allow varying interactions and encounters between the simulation and the participant, providing a wide range of learning capabilities (Piccoli et al., 2001).

With the integration of computer simulations with traditional instruction, teachers need to understand how these interactions affect the student's ability to produce a quality artifact, or their performance outcomes. Bowen and DeLuca (2015) reported that the sequence of delivery for the content and simulation has an impact on student performance outcomes. Research also demonstrates that students with varying levels of content knowledge have different performance outcomes (Bowen et al., 2016; Blanchard et al., 2010). Students with higher levels of content knowledge can initially have significantly better performance outcomes. However, students with less content knowledge perform equally well if given enough time and opportunities to engage in the simulation activity (Bowen et al., 2016). The current research study builds on previous work by looking further into the specific nature of how students with different levels of content apply their knowledge and how this impacts their performance outcomes in a virtual simulation environment.

Modeling and Simulation

Computer simulations in a virtual environment allow humans to extend their capabilities within the engineering design process. de Jong and van Joolingen (1998) defined computer simulation as "a program that contains a model of a system (natural or artificial) or a process." Computer simulation and computer-aided three-dimensional design allow students to learn advanced mathematical and science concepts and engineering principles such as simple machines, mechanical advantage, and truss design (Jacobson, Taylor, et al., 2013; Smith, 2003). Integrating simulation into inquiry-based science laboratory activities has been shown to increase student achievement and long-term retention compared to traditional laboratory instruction (Blanchard et al., 2010; Jacobson, Taylor, et al., 2013; Louca & Zacharia, 2012). Engaging in simulation activities allows students to create virtual representations of physical objects and develop an understanding of how these objects behave and interact with each other (Lamoureux, 2009; Magana et al., 2019; Piccoli et al., 2001; Vieira et al., 2018). Users can examine performance outcomes after establishing the criteria and constraints from which to work (Smith & Pollard, 1986). The design can be adjusted based on the results, and further iterations can be performed. Students can experiment with different scenarios, problem-solving, and decision-making tasks more efficiently; it is more cost-efficient and creates time for increased iterations.

In a technology and engineering classroom, modeling and simulation have traditionally been used to apply what the student has learned. Once the student has an understanding of the content knowledge, modeling and simulation are introduced as tools to demonstrate what has been learned. Modeling and simulation allow students to run multiple iterations and test a greater number of models before committing to a final solution. By incorporating modeling and simulation into the lesson, students can create multiple virtual models and test and redesign them as necessary (Deal, 2002; Piccoli et al., 2001). This is an efficient method of applying what the student has learned because the modeling and simulation process can help create a more meaningful connection to the content (Bowen & Peterson, 2019). When used in combination, modeling and simulation, along with physical models, can be highly beneficial in expanding student learning to illustrate engineering and design concepts (Clark & Ernst, 2006; Ernst & Clark, 2009; Jaakkola et al., 2011; Newhagen, 1996; Smith & Pollard, 1986; Zacharia, 2007).

Knowledge Application

In technology and engineering-based middle-grade classrooms, bridge building and CO_2 cars are two popular design activities. However, since both projects require consumable materials, it would be extremely difficult for a classroom teacher to spend the time and materials necessary for students to participate in the testing, evaluation, and redesign steps of the engineering design process using only physical models as the artifact. Therefore, students commonly use virtual modeling to apply their knowledge to all the steps of the engineering design process and complete the learning loop for testing and redesign (Michael, 2000; Swinson et al., 2016). During the simulation activity, ideally, students will apply what they have learned through classroom instruction to achieve the desired performance outcomes. However, given the need for the students to develop multiple iterations of design, their level of knowledge may reach a limit. When this limit is reached, students may use alternative problem-solving methods such as trial and error.

A trial and error approach is typically used as one method of problem-solving when the novice learner is forced to select from many alternative outcomes (Noble, 1957). Experts (control group in this study) tend to use a "breadth-first" strategy that looks at a comprehensive approach to the problem (Cross, 2004; Ho, 2001) as well as making connections to concepts and key design decisions (Crismond, 2001). Novices (experimental group in this study), on the other hand, approach problems with a "depth-first" strategy by performing detailed analysis of subcomponents before moving on to the next one, creating an overall less efficient approach (Ahmed & Wallace, 2004; Ahmed et al., 2003; Atman et al., 2007; Cross, 2004; Ho, 2001). However, given additional time for alternative problem-solving techniques, such as trial and error, a novice could "catch up" to an expert (Bowen et al., 2016). Novices invest more time in clarification of the elements of the problem-solving process (Atman et al., 1999, 2007; Gunther & Ehrlenspiel, 1999). This alternate problem-solving method begins when the limit of theoretical knowledge has been reached and does not follow any sort of prescribed methodology (Callander, 2011). A student using this method may have little understanding of the problem area, so theory often provides limited guidance (Callander, 2011). Although a specific methodology is not uniformly used, trial and error processes are rarely random (Hull, 1939). When a student realizes they will not benefit from a randomly selected choice, they will reject that option, therefore learning by the trial and error process (Jones, 1945; Young, 2009). This approach is not always careless but can be organized and logical. Students that engage in computer simulation activities before gaining significant knowledge about the content, have been shown to demonstrate high levels of academic performance in computational model-based learning environments (Bowen & DeLuca, 2015; Bowen et al., 2016; Jacobson, Kim, et al., 2013). As learning occurs through the trial and error process, students will show a strengthening of the correct tendencies and a weakening of the incorrect tendencies (Hull, 1939). Callander (2011, p. 2277) states, "The search for good outcomes is frequently guided by trial and error." Students will experiment with alternative outcomes, maintaining the latest approach only if it provides an advantage. The seeking out of new strategies and ideas allows this method to help a student find new knowledge (Young, 2009).

Research Questions

Current research shows that when appropriately integrated, computer simulations can: enhance student learning achievement (Betz, 1995); be as effective as hands-on lab experiences in teaching scientific concepts (Chao et al., 2017; Choi & Gennaro, 1987); enhance students' problem-solving skills (Gokhale, 1996); and allow students to see the interrelatedness of various functions and how they contribute to performance outcomes (Lamoureux, 2009). However, there is little research relating how the level of content knowledge gained by the student correlates with their ability to demonstrate knowledge application within the engineering design process, particularly at the secondary level (Rutten et al., 2012). The methodology of the current study was designed to determine the significance of content knowledge as a factor in achieving performance outcomes in a virtual simulation environment for middle school students. Previous research by Bowen et al. (2016) served as the foundation for this study. Their research proved that students with higher levels of content knowledge initially have significantly better performance outcomes; however, students with less content knowledge perform equally well if given enough time and opportunities to engage in the simulation activity. The current research implements a design that determines more specific aspects of how students are applying their knowledge of the content to design a truss. In addition, the researchers want to know if it can be determined at which point the experimental group's performance "catches up" to the control group once enough iterations are performed. As previously mentioned, trial and error may be one of the components integrated throughout the application of the design process. The intent of this study is not to determine the extent to which content knowledge application and trial and error are integrated throughout the design process; rather the purpose of this study is to determine the differences in various aspects of the performance outcomes when the content knowledge is controlled between two groups of participants. The context of the engineering problem in this study is truss design using a virtual bridge simulation program. This study was designed to answer the following research questions:

1. How does the introduction of content knowledge affect performance outcomes of designed-based virtual bridge models in a computer modeling and simulation environment for middle school students?
2. Can it be determined at which point the performance outcomes of the control and experimental groups is not statistically different?

Methodology

The methodology of this study follows a similar design to that of Bowen et al. (2016). The purpose of this research is to measure if a significant difference exists in how students apply their knowledge when modeling a virtual bridge design through computer simulations. The primary learning goal for the students was to demonstrate knowledge application in terms of a performance outcome, as measured by the efficiency of the students' virtual bridge models. Classrooms of students were divided into control and experimental groups. The control group engaged in the simulation program as it was designed, with the content built into the program functions. The experimental group did not participate in the portion of the program that provided background knowledge of the truss design content. Then, by analyzing the performance of the virtual models, the researchers measured how this difference in content knowledge affected the student's ability to apply the knowledge. The following sections describe the methodology of the research, how the content was differentiated between the groups, the computer simulation activity, and how the simulation program was used to collect data.

Modeling and Simulation Software Description

Many simulation programs exist for integrating virtual modeling of bridges into secondary classrooms. For this particular research project, a software platform was used that focuses on truss design. Two versions of the application are available for secondary classrooms, one for the middle school level and one for the high school level. The difference between the two versions is the amount of mathematics required to complete the research section and the formative assessments built into the program. The high school version uses more advanced mathematics to solve for the different types of forces in each of the bridge truss members. The middle school version uses fewer mathematical concepts and focuses

Control:	Pre-test > Introduction > Research > Virtual Tutorial > Engineering > Post-test
Experimental:	Pre-test > Paper Tutorial > Engineering > Post-test

Figure 1. Sequencing for Control and Experimental Groups

Group	Avg. % of content sections visited	Total avg. time spent in content sections (min.)
Control	54.0	27.1
Experimental	12.7	1.9

Table 1. Content visited and time on task.

on conceptual knowledge of bridge design and efficiency. This study used the middle-school version of the application.

The modeling and simulation software is a web-based program that students can access anywhere with an internet connection by logging in with a unique username and password. The program begins by having the student read through an introduction section providing background knowledge about general bridge design principles. This section describes basic engineering concepts such as truss components, factors of safety, forces, and other definitions related to basic bridge design. The program then leads students through a research section that provides more detailed information about truss design and bridge efficiency. This is when students learn how specific aspects of building a truss create a more efficient design. Formative assessments, taken only by the control group, are built in throughout the research section to check the student's understanding of the content. Formative assessments are not meant to be graded but give the teacher feedback on the students learning progress (Keeley et al., 2005). The software has a teacher control center, allowing the teacher to monitor the student's progress on each section of the program and the formative assessments. Once the student completes the research section, a tutorial demonstrates the use of the specific program functions needed to design a truss. The tutorial is followed by the engineering section, allowing students to begin designing their bridges. Students can test different designs to see how much weight the truss can support before failure. Each test is recorded as an iteration, and based on the specifications predetermined by the teacher, these iterations can be within specifications or out of specifications. Once the student has decided on a final design, a template of the truss can be printed for building the physical model. Please refer to Bowen and DeLuca (2015) for a more detailed description of the software.

Once the teacher introduced the bridge-building project, students were allowed to proceed through the program at their own pace. During the project time, the teacher had little influence on how the students interacted with the program, except to answer general questions. Since both groups had access to a tutorial, either through the virtual program or a paper tutorial from which to learn the program functions, minimal guidance was provided by the teacher. Once the teacher thought the students had ample time to complete the project, a time limit was established in order to bring closure to the project activities.

Research Participants

The participants in this study were from a middle school, serving approximately 1,200 students in grades 6-8, located in the upper mid-west of the United States. All students in the school are required to register for a STEM-based technology education course for one quarter. The students in this study were in 8th grade. Due to the course lasting nine weeks, the classroom teacher had a new student roster each quarter. There were four 8th-grade classes each quarter. The study involved all four 8th grade classes throughout the day and spanned all eight quarters of the 2013-2014 and 2014-2015 school years. Two classes each quarter were formed into a control group and experimental group, with two classes each quarter being in each group. Each quarter, classes were randomly selected to be in the control and experimental groups. The sample size is 230 students for the control group and 227 students for the experiential group. The same teacher taught each section of the class. The teacher was available to answer questions during the project but was not involved in content delivery since the program had built-in content. The students also worked individually during the project; students did not work in groups, and there was no intentional peer interaction between classmates during the project. There was no intentional grouping of the students by the school and each class was of mixed ability. However, due to measures beyond the researchers' control that determine student scheduling, this study is quasi-experimental and assumes non-parametric conditions.

Control and Experimental Group

Before research activities, the researchers obtained student and parental consent at the beginning of each quarter. The control and experimental groups took a pre-test at the onset of research activities. After the pre-test, students in both groups received login information for the modeling and simulation program. The difference between the control and experimental groups was which

Element	Description
Assessments (Table 3)	
Pre-test	# correct out of 15
Post-test	# correct out of 15
Difference	Change in score between pre- and post-test
Virtual Model Efficiencies (Table 4)	
First overall model efficiency; in-spec or out-of-spec	Total weight held divided by weight of the bridge
Best overall model efficiency; in-spec or out-of-spec	Total weight held divided by weight of the bridge
First in-spec model efficiency	Total weight held divided by weight of the
Best in-spec model efficiency	Total weight held divided by weight of the
Virtual Model Iterations (Table 5)	
In-Spec Iterations	# of total tests within specifications
Out-of-Spec Iterations	# of total tests out of specifications
Total Iterations	# of in-spec and out-of-spec tests combined
Iterations to get to 1st in-spec model	# of total tests to get to the first in-spec model
Iterations to get to best in-spec	# of total tests to get to the best in-spec model
Iterations to get to best overall	# of total tests to get to the best overall model
In-spec iterations to get to best in-spec model	# of in-spec tests to get to the best in-spec model
Virtual Model First Iterations (Table 6)	
First iterations that are in-spec	# students with first overall test in-spec

Table 2. Elements of the statistical analysis.

section of the program the students began. In this study, the control group is defined as the students who engaged in all aspects of the simulation program as it is intended to be used. The control group proceeded through each section of the program in sequence: introduction, research, virtual tutorial, and engineering. The experimental group skipped the introduction, research, and virtual tutorial sections and proceeded directly to the engineering section. Therefore, the experimental group is not engaging with the sections of the program that provide content knowledge, while the control group is exposed to this knowledge. Therefore, the control group gains content knowledge by initially engaging in the introduction and research sections, whereas the experimental group does not. Since the experimental group is skipping directly to the engineering section, these students were given a paper copy of the tutorial. Due to some of the content knowledge being embedded within the virtual tutorial, a paper copy was provided to the experimental group allowing these students to learn how to use the program functions for designing their bridges without the risk of being exposed to any of the built-in content. Once all of the students had the opportunity to complete the teacher's expectations for the virtual simulation portion of the students' projects, both groups took a post-test. A summary of the sequencing of activities for each group is shown in Figure 1.

It is important to note that the design of the simulation platform does not prevent students from reading previous sections of the program or switching back and forth between the engineering and research sections. The teacher instructs the experimental group to proceed directly to the engineering section once logged in and to use the paper tutorial to learn the design functions of the icons. However, there is not a teacher-controlled setting to prevent students from switching back and forth between the content and engineering sections. Data shows some students in the experimental group went back to previous sections but did not spend much time in the content sections (see Table 1). There are 17 total sections within the program that contain content knowledge, including general reading materials, formative assessments, and the virtual tutorial. Although some students in the experimental group visited research sections, the results show a large disparity in both the number of sections visited as well as the time spent in sections that contain content knowledge. Therefore, the researchers are confident the ability of the experimental group to access the research section of the program did not adversely affect the results of this study.

Data Collection and Analysis

Due to the design of the software, the researchers were able to access various pieces of data from the program. Details of an iteration are recorded each time a student tests a virtual model. This data includes the time and date, whether it was within specifications or not, the efficiency, the random student identifier, and the class year and period for each iteration. The data was downloaded into a spreadsheet that was used to perform the statistical analysis. Table 2 describes the elements of student performance that were included as part of the statistical analysis. The traditional pre- and post-tests were used as a measure of content knowledge. Each test consisted of 15 multiple-choice items developed by the researchers based on the content covered through the introduction and research sections of the program. Two experts in the field reviewed the questions' content separately and collaboratively. This review process resulted in a pre- and post-test that the experts agreed was representative of the knowledge students are intended to gain through the introduction and research sections of the program. Both instruments had a high level of internal consistency, as determined by a Cronbach's alpha: pre-test, α=.90; post-test, α=.91 (Taber, 2018).

After data collection, a statistical analysis using SPSS determined any significant differences between the control and experimental groups for the variables listed in Table 2. Due to the study's two independent samples and non-parametric conditions, the Wilcoxon Rank Sums Test was used for the statistical analysis in Tables 3-8, except for Table 6. Since determining how many first iterations were within specifications is a dichotomous variable, Table 6 only reports descriptive data.

Results

The results in tables 3-6 report data used to answer research question 1: How does the introduction of content knowledge affect performance outcomes of designed-based virtual bridge models in a computer modeling and simulation environment for middle school students? Table 3 reports the results of the statistical analysis for the pre- and post-tests.

The results show there was no statistically significant difference between the two groups for pre-test scores. This analysis established a baseline for having no significant differences in knowledge before using the simulation program. However, there was a statistically significant difference in post-test scores and in the increase between pre- and post-test performance. The results for the statistical analysis of the virtual model efficiencies are shown in Table 4.

From these results, the control group had a significantly higher efficiency for the first virtual model design, both when accounting for in-spec only models and also when considering models tested with both in-spec and out-of-spec designs. There was not a significant difference in the best in-spec or best overall (accounting for in-spec and out-of-spec) virtual model efficiencies. Table 5 shows the statistical results when comparing various aspects of

Item	N	Min	Max	Mean	Std. Dev.	Sum of Ranks	Z	p-value
Pre-test								
Control	227	1	13	8.07	2.35	52508	-0.793	0.428
Experimental	225	0	13	7.90	2.32	50963		
Post-test								
Control	221	2	15	9.84	2.36	52303	-3.076	0.002*
Experimental	215	2	14	9.08	2.38	42964		
Difference (Post minus Pre)								
Control	218	-5	8	1.73	2.36	50561	-2.520	0.012*
Experimental	215	-5	7	1.17	2.49	46655		

*significant at α = .05

Table 3. Statistical analysis of pre- and post-assessments

Item	N	Min	Max[1]	Mean	Std. Dev.	Sum of Ranks	Z	p-value
First overall model efficiency; in-spec or out-of-spec								
Control	212	7	10872	1872	1310	51168	-4.648	<0.001*
Experimental	214	1	97399	1888	6681	39783		
Best overall model efficiency; in-spec or out-of-spec								
Control	217	1011	59010	5327	5612	45082	-1.773	0.076
Experimental	219	1372	109020	7418	13021	50184		
First in-spec model efficiency								
Control	212	932	4986	2461	852	51760	-5.118	<0.001*
Experimental	214	609	4875	2056	810	39191		
Best in-spec model efficiency								
Control	212	1021	5307	3756	1124	45397	-0.106	0.915
Experimental	214	1149	5380	3707	1211	45554		

*significant at α = .05
1. outliers may exist due to very high values when bridge designs are out-of-spec

Table 4. Statistical analysis for virtual model efficiencies.

Item	N	Min	Max	Mean	Std. Dev.	Sum of Ranks	Z	p-value
In-spec iterations								
Control	217	0	74	11.68	11.39	43518	-2.965	0.003*
Experimental	219	0	55	14.48	11.81	51749		
Out-of-spec iterations								
Control	217	0	62	11.82	11.31	42920	-3.419	0.001*
Experimental	219	0	70	14.79	11.66	52346		
Total iterations								
Control	217	1	108	23.50	19.37	42278	-3.906	<0.001*
Experimental	219	1	91	29.26	19.05	52988		
Iterations to get to 1st in-spec model[1]								
Control	182	1	54	10.27	9.38	30308	-3.436	0.001*
Experimental	189	1	66	12.89	9.67	38698		
Iterations to get to best in-spec model								
Control	212	1	107	20.49	17.95	40412	-3.818	<0.001*
Experimental	214	1	88	25.36	17.07	50539		
Iterations to get to best overall model								
Control	217	1	78	16.34	15.67	43246	-3.171	0.002*
Experimental	219	1	79	20.05	16.07	52021		
In-spec iterations to get to best in-spec model								
Control	212	1	72	9.43	10.32	41948	-2.616	0.009*
Experimental	214	1	47	11.69	10.63	49004		

*significant at $\alpha = .05$
1. Excludes students that did not have an in-spec model

Table 5. Statistical analysis comparing virtual model iterations

Group	N	In-Spec #	In-Spec %	Out-of-Spec #	Out-of-Spec %
Control	217	23	10.6	194	89.4
Experimental	219	8	3.7	211	96.3

Table 6. Descriptive analysis of first iterations.

the different iterations performed by the two groups.

When considering the number of iterations, the experimental group had a significantly higher number of in-spec, out-of-spec, and total iterations. Since the experimental group skipped the introduction and research sections and proceeded directly to engineering section of the program, these students had more time to design virtual models. The researchers believe this resulted in the experimental group performing significantly more iterations than the control group. The results show it took the experimental group significantly more iterations to get to their first in-spec model, best in-spec model, best overall model, and best in-spec model. The test for determining how many iterations it took for students to create their first in-spec model excluded the students that did not have an in-spec iteration. This is because the researchers were interested in knowing how long it took students from either group to create an in-spec model, meaning they would need at least one in-spec model to be included in the analysis of this specific criteria. Table 6 shows the results of how many students were able to create a virtual model within specifications on their first iteration. From the data, 10.6% of the control created an in-spec model on their very first test, compared to 3.7% for the experimental group. This means almost 3 times the number of students in the control group were able to create an in-spec iteration on their first test compared to the experimental group.

The results in tables 7 and 8 report data used to answer research question 2: Can it be determined at which point the performance of the control group and the experimental group is not statistically different? Table 7 shows the results from comparing each individual iteration of in-spec models only.

The results show the control group's virtual designs are significantly more efficient than the experimental group's through iteration 5. On the 6th iteration, the virtual designs between the groups are no longer significantly different. The data was analyzed through 50 iterations and there were no significant differences beyond iteration 5 that met the assumptions of the statistical analysis. There were significant differences at iteration 36 and 38, but at that iteration the sample size for both groups was below 30 students. Therefore, only the first 10 iterations are shown. Table 8 shows the results from comparing each individual overall iteration, which includes both in-spec and out-of-spec iterations.

The results show the control group's virtual designs are significantly more efficient than the experimental group's through iteration 7. On the 8th iteration, the virtual designs between the groups are not significantly different, however, they become significant again for iterations 9 and 10. The data was analyzed through 50 iterations and there were no significant differences beyond iteration 10. Therefore, only the first 10 iterations were reported.

Discussion

The purpose of this research was to explore various aspects of the students' performance in a simulation environment based on different levels of content knowledge and to determine at what point these variations of knowledge produce outcomes that were not significantly different. The results show there is a significant difference in the means of the post-test scores and in the difference between the pre- and post-tests between the two groups. This is expected, and supported by previous work (Bowen & DeLuca, 2015; Bowen et al., 2016), since the control group was exposed to the content through the introduction and research sections of the program while the students in the experimental group were not. Although this result is expected, the significantly higher post-test scores for the control group demonstrate the need to engage the students in the content to meet standards, such as those in the Standards for Technological Literacy (International Technology Education Association; 2000). The results also show the control group had significantly higher means of the first virtual bridge design efficiency; both when using only in-spec iterations and when combining iterations that are both in-spec and out-of-spec. This demonstrates that once the students gain initial knowledge about truss design, this knowledge is applied during the initial design of their bridge. However, there is not a significant difference in the means of the best virtual model efficiencies between the two groups. This suggests there are other factors that contribute to the student's application of knowledge throughout the simulation activity. To answer the first research question, "How does the level of content knowledge affect various aspects of knowledge application to achieve the performance outcomes of designed-based virtual bridge models in a computer simulation environment for middle school students?", the results demonstrate content knowledge is a significant factor when first designing a truss, but at some moment within the activity, there is no significant difference in the most efficient design. The students in the experimental group did not read the introduction or engage in the research sections of the program. Therefore, since content knowledge was not part of the instructional process, these students had to rely on different strategies to increase their design efficiency when

Item	N	Min	Max	Mean	Std. Dev.	Sum of Ranks	*Z*	*p*-value
Iteration 1								
Control	212	932	4986	2461	852	51760	-5.118	<0.001*
Experimental	214	609	4875	2056	810	39191		
Iteration 2								
Control	197	635	5067	2531	1028	44704	-4.201	<0.001*
Experimental	206	659	5138	2148	831	36702		
Iteration 3								
Control	182	0	5139	2625	1087	38259	-3.355	0.001*
Experimental	198	156	5268	2277	971	34131		
Iteration 4								
Control	171	874	5230	2782	1085	33518	-3.392	0.001*
Experimental	182	446	5211	2404	1034	28964		
Iteration 5								
Control	153	804	5184	2835	1130	27275	-2.763	0.006*
Experimental	172	446	5270	2511	1141	25700		
Iteration 6								
Control	133	522	5241	2783	1175	20017	-1.133	0.257
Experimental	155	446	5247	2613	1105	21600		
Iteration 7								
Control	124	522	5241	2829	1132	17849	-1.223	0.221
Experimental	150	418	5249	2684	1151	19827		
Iteration 8								
Control	118	884	5234	2853	1085	15985	-0.372	0.710
Experimental	148	446	5316	2850	1222	19526		
Iteration 9								
Control	104	0	5307	2848	1227	12431	-0.093	0.926
Experimental	135	914	5322	2874	1224	16250		
Iteration 10								
Control	98	657	5303	2901	1179	11180	-2.180	0.828
Experimental	127	896	5327	2922	1306	14246		

*significant at α = .05

Table 7. Statistical analysis comparing in-spec virtual model iterations.

Item	N	Min	Max[1]	Mean	Std. Dev.	Sum of Ranks	*Z*	*p*-value
Iteration 1								
Control	212	7	10872	1872	1310	51168	-4.648	<0.001*
Experimental	214	1	97399	1888	6681	39783		
Iteration 2								
Control	209	96	22220	2073	2001	51181	-5.570	<0.001*
Experimental	213	1	63612	1658	4456	38073		
Iteration 3								
Control	202	0	10872	2009	1641	46680	-3.915	<0.001*
Experimental	212	1	97399	2083	7120	39226		
Iteration 4								
Control	199	6	17642	2093	1969	45014	-3.435	0.001*
Experimental	211	0	97399	2652	8732	39242		
Iteration 5								
Control	194	27	10872	1941	1669	42261	-2.630	0.009*
Experimental	209	0	58629	2333	6354	39145		
Iteration 6								
Control	181	1	13130	2053	1808	38274	-2.878	0.004*
Experimental	206	0	50617	1885	3779	36804		
Iteration 7								
Control	174	6	12640	2013	1635	35195	-2.372	0.018*
Experimental	201	0	12308	1767	1747	35305		
Iteration 8								
Control	167	3	48281	2117	3768	32077	-1.509	0.131
Experimental	198	0	21269	2037	2502	34719		
Iteration 9								
Control	159	31	6299	1949	1203	30125	-1.986	0.047*
Experimental	195	4	28140	2037	2631	32711		
Iteration 10								
Control	155	25	59010	2446	4771	29484	-2.896	0.004*
Experimental	190	0	34359	2038	2905	30201		

*significant at α = .05
1. outliers may exist due to very high values when bridge design does not meet specs

Table 8. Statistical analysis comparing overall virtual model iterations.

negotiating through multiple iterations.

When analyzing the number of iterations, the experimental group had significantly more iterations, for in-spec, out-of-spec, and overall, and it took this group significantly more iterations to test an in-spec model as well as design their most efficient model. Since this group did not receive content, these students took longer to get to a bridge efficiency that was not significantly different from the control group. This idea supports previous research findings that students with less content knowledge have a more difficult time making connections, preventing them from effectively applying their knowledge (Mentzer, 2014; Mentzer et al., 2015). In table 5, the control group had three times more of the number of first iterations that were within specifications than the experimental group. The control group received the content and better understood design parameters, such as criteria and constraints. They were able to apply this requirement to a significantly higher number of their first iterations. The experimental group proceeded directly to the engineering section, which means these students spent their entire simulation project time in the design, test, and redesign phases. Therefore, these students had significantly more iterations because they generally spent more time on the truss design portion of the program. Therefore, these students were able to figure out what increases the efficient of their truss by manipulating their design in the program, resembling more of a trial and error approach. By using this approach, students in the experimental group were able to learn what creates a more effective truss design without applying learned knowledge of truss design. This is also supported by findings in the larger variance of both the first and best model efficiencies, both in or out of specifications. This provides evidence these students are testing truss designs that do not follow proper criteria and constraints since models outside of required specifications can have abnormally large efficiencies. This supports findings from previous studies that report modeling and simulation has varied results in their ability to increase achievement in both content knowledge and knowledge application (Bowen & DeLuca, 2015; Bowen et al., 2016; 2018; Chao et al., 2017; Gokhale, 1996; Jaakkola et al., 2011; Rutten et al., 2012).

Clarke et al., (2005) determined that how activities are integrated in the classroom have an impact on student learning, and therefore teachers need to make informed choices about curriculum design. Students will engage in the design process differently based on the collection of various knowledge and skill sets, resulting in a variance of design process efficiency (Crismond & Adams, 2012). The results of the current project support the importance of properly assessing the learning outcomes of a design activity and how instructors choose to integrate modeling and simulation with traditional instruction (Yadav et al., 2016). The results show that given enough opportunities within a simulation environment, a student with less content knowledge can achieve similar performance outcomes compared to a student with greater content knowledge. As expected, exposing students to content knowledge produces significantly higher outcomes on traditional assessments as shown by the difference in pre- and post-test scores. This initial higher level of content knowledge produces significantly higher initial bridge efficiencies. However, given enough opportunities, students with less content knowledge can produce an outcome that is not significantly different from students with more content knowledge. Therefore, using performance outcomes as the only measure of student knowledge would not be an accurate assessment of their content knowledge. By skipping the content, students would not engage in the necessary standards to have a fundamental understanding of the underlying concepts.

Tables 6 and 7 report the results from analyzing each iteration to see if can be determined at which part of the design process the experimental group's design is not significantly different from the control group. When only considering the in-spec iterations, the control group's designs are significantly more efficient through iteration 5. Beginning with iteration 6, the designs are no longer significantly different. When considering overall iterations, the control group's designs are significantly different through iteration 10, with the exception of iteration 8. The exception of iteration 8 could reasonably be expected because a student's gain in knowledge is not perfectly linear, and the variations in virtual design efficiencies would allow significant differences to fluctuate during the design process. To answer the second research question, "Can it be determined at which point the performance of the control group and the experimental group is not statistically different?", it takes approximately 5-10 iterations for the experimental group's design to no longer be significantly less efficient than that of the control group. This analysis demonstrates that content knowledge allows for early onset efficiency in the design process. However, after several iterations, students with less content knowledge can produce models that are not significantly different.

Conclusion

From the results, the researchers have concluded that content knowledge plays a significant factor in the initial phase of applying knowledge in the simulation environment. Students with this initial knowledge take less iterations to produce models within specifications and designs that are significantly more efficient. However, students with less initial content knowledge can design virtual models that are not significantly different from students with more content knowledge if given enough iterations. From the design of this study, it takes approximately 5-10 iterations for the students with less content knowledge to gain the appropriate knowledge to create designs that are not significantly different from those of students with greater content knowledge. These conclusions are important when determining the objective of the students' project activities and how to balance the delivery of content knowledge versus how students are applying their knowledge during a design activity involving virtual simulation. The results of this study also demonstrate the need for a variety of assessments. If a student with less understanding of the content is assessed through the outcomes of a modeling and simulation activity, it is possible for them to perform similar to a student with greater content knowledge. This research demonstrates the critical need for instructors to design assessments to appropriately measure the intended knowledge and performance objectives.

Limitations and Future Research

Although the results of this study demonstrate how students are applying different aspects of knowledge throughout engineering-based simulation activities, there is a need for further studies to gain a better understanding of student performance and to address limitations in the research design. The population used in this study was from one school site with approximately 76% of the students being Caucasian, 9% Hispanic, and 15% combined of African America, Asian, and Native American. Conducting research at other school sites will provide additional data to help determine how the results from this study compare to other student populations and geographic locations. In addition, students in the experimental group were able to access sections of the program that contained content. Although the amount of time spent in content sections was low for the experimental group, additional measures need to be addressed within the research design to better account for how this may influence the results. Regarding content, this study only addresses virtual simulations within a bridge building context. Other studies are needed to determine how students are using virtual simulations for other types of content knowledge in other subject areas. Overall, knowing how students are applying content knowledge and at what point the two groups' designs are not significantly different informs the research base and creates additional discussions necessary in the field. Further research will produce more efficient methods of integrating traditional content and virtual simulations to better understand how students apply their knowledge, therefore improving the learning outcomes for students in a simulation environment.

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