The Impact of Content Knowledge on Performance Outcomes for Middle School Students in a Design-Based Simulation Environment

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Abstract

Simulation modeling is a common tool used in many secondary schools offering technology and engineering courses. The performance of the final design is usually dependent upon the student's ability to apply the knowledge learned through direct instruction from the teacher. This study measures the differences in the outcomes of a performance-based activity between students with varying levels of content knowledge within a simulation environment. The results show that students have significantly better performance outcomes when beginning the activity with greater content knowledge. However, students with less content knowledge perform equally well if given enough time and opportunities to engage in the simulation activity.

Introduction

In secondary technology and engineering courses, students typically develop an artifact to represent the application of content knowledge. The purpose of this artifact is to demonstrate the student's understanding of the knowledge previously delivered by the classroom teacher (Mentzer, 2011). By engaging in the problem-solving process, students 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 knowledge application. One of the tools common in a technology and engineering classroom is computer simulation. Simulation activities allow students to engage in the iterative nature of the design process without the time consuming aspect of constructing multiple physical models. However, with the integration of computer simulations with traditional instruction, teachers need to understand how these interactions affect student performance outcomes.

Simulation Modeling

Computer simulation, along with computer-aided three-dimensional design, allows students to learn advanced mathematical and science concepts, as well as engineering principles such as simple machines, mechanical advantage, and truss design (Jacobson, Kim, Pathak, & Zhang, 2013; Jacobson, Taylor, Richards, & Lai, 2013; Smith, 2003). Through simulation activities, students are able to create virtual representations of physical objects, increasing the understanding of how these objects behave and relate to each other (Lamoureux, 2009). Virtual learning environments allow the participants to engage in a variety of interactions and encounters and provides a wide range of learning capabilities (Piccoli, Ahmad, & Ives, 2001). Students can experiment with different scenarios, problem solving, and decision-making tasks with little risk and without wasting resources.

Once the theoretical knowledge is learned, simulation modeling has traditionally been used as a tool to demonstrate the application of the learned theory. Simulation modeling allows students to run multiple iterations and test a greater number of models before committing to a final solution. By using simulation modeling, students can create multiple virtual models, as wells as test and redesign them as necessary (Deal, 2002; Piccoli et al., 2001).This is an efficient method of knowledge application because students can gain knowledge of the authentic application of theory and course content. When used in combination, simulation modeling and physical models can be extremely beneficial in expanding student learning to illustrate engineering and design concepts (Clark & Ernst, 2006; Ernst & Clark, 2009; Jaakkola, Nurmi, & Veermans, 2011; Newhagen, 1996; Smith & Pollard, 1986; Zacharia, 2007).

Knowledge Application

In technology and engineering middle grade classrooms, bridge building and CO2 cars are two popular design activities. However, since both of these 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. During the simulation activity, ideally students will apply the content knowledge gained through classroom instruction to achieve the desired simulation performance outcomes. However, given the need for continuous engagement and development of multiple iterations of design, their level of content knowledge may reach its limit. Students are gaining various aspects of knowledge throughout the entirety of the design process, including but not limited to, theoretical knowledge, procedural knowledge, knowledge of variables and constraints, and knowledge application. It also includes process knowledge that cannot be directly linked to a learned concept.

Research Question

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 (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 related how the level of content knowledge gained by the student correlates to their ability to demonstrate knowledge application within the engineering design process, particularly at the secondary level (de Jong, & van Joolingen, 1998; Rutten, van Joolingen, & van der Venn, 2012). The methodology of the current study was designed to determine how much content knowledge is a factor in achieving performance outcomes in a virtual design simulation environment for middle school students. Previous research by Bowen, DeLuca, and Franzen (2016) served as the foundation for this project. 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 project implements a design that determines more specific aspects of how application knowledge is being utilized by students with varying levels of content knowledge. 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 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?

Methodology

The methods of this research project follows a similar design to that of Bowen et al. (2016). The purpose is to measure if significant differences exist in various aspects of knowledge application when students integrate content knowledge and virtual bridge design through computer simulations. Performance outcomes were measured by the efficiency of virtual bridge models. Classrooms of students were divided into control and experimental groups. Each group received a different level of content knowledge throughout the simulation program. Then, by analyzing the performance of the virtual models, the researchers measured how different levels of content knowledge affected the student's ability to apply the learned knowledge. The following sections describe the methodology of the research project, levels of student content knowledge, the computer simulation activity, and the data collection and analysis process.

Structures Virtual Platform Description

Many simulation programs exist for integrating virtual modeling of bridges into secondary classrooms. For this particular research project, the software application Structures 2.0, published by Whitebox Learning, was used as the virtual simulation platform. There are two versions of the Structures 2.0 application available for secondary classrooms; one for middle school level and one for high school level. The difference in the two versions is the amount of mathematics required to complete the research section and 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 less mathematical concepts and focuses on overall conceptual knowledge of bridge design and efficiency. This study used the middle-school version of the Structures 2.0 application.

The Structures 2.0 platform is a web-based platform that students can access anywhere with internet access 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 provides basic engineering concepts such as truss components, factors of safety, forces, and other content-specific definitions related to bridge design. The program then leads students through a *research* section that provides detailed information about truss design and bridge efficiency. This is when students gain an in-depth view of how specific aspects of building a truss creates a more efficient design. Formative assessments are built in throughout the research section to check the students' understanding of the content. The teacher control center allows the teacher to monitor the students' progress on the formative assessments and how much time is spent on each section throughout the program. Once a student completes the research section, a virtual tutorial demonstrates the use of the specific program functions needed to design a truss. The tutorial is followed by the *engineering* section, which allows students to design their own bridges. Students can test different designs to see how much weight the bridge 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 a student has decided on a final design, a template of the truss can be printed for building a physical model. Please refer to Bowen and DeLuca (2015) for a more detailed description of the Whitebox Learning Structures 2.0 platform.

Research Participants

The participants in this research project were from a middle school, serving grades 6-8, located in the upper midwest of the United States. All students in the school are required to register for a technology education course for one quarter. The students in this study were 8th grade students from one section of this course. Due to the course lasting nine weeks, the classroom teacher has a new student roster each quarter. The research project involved four classes throughout the day and spanned all eight quarters of the 2013-2014 and 2014-2015 school years. Two classes each quarter formed the control group and experimental groups, with two classes each quarter being in each group. Each quarter, classes were randomly selected to be in the control and experimental groups. 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

Prior to research activities, the researchers obtained both student and parental consent at the beginning of each quarter. At the onset of research activities, both the control and experimental groups took a pre-test. After the pre-test, students in both groups were given login information for Structures 2.0. The difference between the control and experimental groups was with which section of the program the students began. The control group proceeded through each section of the program in order; 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 control group was exposed to more content knowledge than the experimental group by initially engaging in the introduction and research sections. Since the experimental group skipped 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 students had the opportunity to complete the teacher's expectations for the virtual simulation portion of the project, both groups took a post-test. A summary of the sequencing of activities for each group is shown in Fig. 1.

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

Experimental: Pre-test > Paper Tutorial > Engineering > Post-test

Figure 1. Sequencing of activities for control and experimental groups.

Data Collection and Analysis

Due to the design of the Whitebox Learning program, the researchers are able to dump various pieces of data from the program. Details of an iteration are recorded each time a student tests a virtual model. Within the data set, each iteration is coded with the time and date, whether it was within specifications or not, model efficiency, random student identifier, and the class year and period. The data was downloaded in a spreadsheet that was cleaned to perform the statistical analysis. Table 1 describes the elements that were included as part of the statistical analysis. The statistical analyses determined any significant differences between the control and experimental groups. Due to the non-parametric conditions of the study, the Wilcoxon Scores (Rank Sums) two-sample test was used for the statistical analysis.

Table 1. *Elements of the Statistical Analysis*

Element	**Description**
Assessments (Table 2)	
Pre-test	# correct out of 15
Post-test	# correct out of 15
Difference (Post minus Pre)	Change in score between pre- and post-test
Virtual Model Efficiencies (Table 3)	
First overall model efficiency;	Total weight held divided by weight of the bridge; includes in-spec and out-of-spec iterations
Best overall model efficiency;	Total weight held divided by weight of the bridge; includes in-spec and out-of-spec iterations
First in-spec model efficiency	Total weight held divided by weight of the bridge; in-spec iterations only
Best in-spec model efficiency	Total weight held divided by weight of the bridge; in-spec iterations only
Virtual Model Iterations (Table 4)	
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 iterations combined

Results

The results of the statistical analyses are shown in tables 2-4. Table 2 reports the results of the statistical analysis for the pre- and post-tests.

Table 2. *Statistical Analysis of Pre- and Post-Assessments*

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 $\alpha = .05$

The results show there was no statistically significant difference between the two groups for pre-test scores. However, there was a statistically significant difference in post-test scores and the increase between pre- and post-test achievement. The results for the statistical analysis of the virtual model efficiencies are shown in table 3.

Table 3. *Statistical Analysis for Virtual Model Efficiencies*

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 $\alpha = .05$

[1] Outliers may exist due to very high values when bridge design does not meet specs

From these results, the control group had a significantly higher efficiency for the first virtual model design; both when accounting for both in-spec and out-of-spec designs combined and also when considering only models tested within specifications. 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 4 shows the statistical results when comparing the number of iterations performed by each group.

Table 4. *Statistical Analysis Comparing Virtual Model Iterations*

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		

*significant at $\alpha = .05$

In regards to 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, resulting in significantly more iterations than the control group.

Discussion

The purpose of this project was to explore various aspects of the students' performance in a simulation environment based on different levels of content knowledge. 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 since the control group was exposed to the content through the introduction and research sections of the virtual platform while the students in the experimental group were not. 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 content knowledge about truss design, this knowledge is being applied during the initial design of their bridge. However, there is not a significance difference in the means of the best virtual model efficiencies between the two groups. This suggests there are other factors contribute to the student's process knowledge throughout the simulation activity. The results demonstrate content knowledge is a significant factor when first designing a truss, but at some moment within the activity, other procedural knowledge is being applied by both groups resulting in no significant difference in the best efficiency. 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 aspects of procedural knowledge to increase their design efficiency when negotiating through multiple iterations.

When analyzing the number of iterations, the experimental group had significantly more in-spec, out-of-spec, and overall 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 spent more time on the truss design portion of the program. Due to the significantly higher number of iterations, students in the experimental group demonstrated knowledge application in the context of the specific program functions. When looking at the results in tables 3 and 4 together, the control group had initial truss designs that were significantly more efficient. However, given enough iterations, the experimental group was able to gain enough application and procedural knowledge to design bridges that were not significantly different from the control group.

Clarke, Ayres, and Sweller (2005) determined that how learning activities are integrated in the classroom have an impact on student learning, and therefore teachers need to make informed choices about curriculum design. The results of this research can have a significant impact on how instructors choose to integrate simulation modeling with traditional instruction as well as how an instructor assesses a student’s performance. The results show that given enough opportunity within a simulation environment, a student with less content knowledge can achieve similar performance outcomes than a student with greater content knowledge. As expected, exposing students to more content knowledge produces significantly higher outcomes on traditional assessments as shown by the difference in pre- and post-test scores. In regards to knowledge application, this initial content knowledge produces significantly greater initial bridge efficiencies. However, given enough opportunities, students with less content knowledge can demonstrate a performance outcome that is not significantly different than 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.

Conclusion

From the results of this project, the researchers have concluded that content knowledge plays a significant factor in the initial knowledge application phase of the simulation performance environment. The researchers believe at some point theoretical knowledge reaches a limit within the knowledge application process, and therefore, over time, may not be significantly different from more knowledge application. These conclusions are important when determining the objective of the project activity and the balance of content knowledge versus knowledge application within a curriculum design when integrating computer simulation.

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