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Teacher Impact on Student Learning Using LC-DLM Implementations in the Classroom

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Work in Progress: Teacher Impact on Student Learning Using LC-DLM Implementations in the Classroom

Our team has developed Low-Cost Desktop Learning Modules (LCDLMS) as tools to study transport phenomena aimed at providing hands-on learning experiences. With an implementation design embedded in the community of inquiry framework, we disseminate units to professors across the country and train them on how to facilitate teacher presence in the classroom with the LC-DLMs. Professors are briefed on how create a homogenous learning environment for students based on best-practices using the LC-DLMs. By collecting student cognitive gain data using pre/posttests before and after students encounter the LC-DLMs, we aim to isolate the variable of the professor on the implementation with LC-DLMs. Because of the onset of COVID-19, we have modalities for both hands-on and virtual implementation data. An ANOVA whereby modality was grouped and professor effect was the independent variable had significance on the score difference in pre/posttest scores ($p<0.0001$) and on posttest score only ($p=0.0004$). When we divide out modality between hands-on and virtual, an ANOVA with an F-test using modality as the independent variable and professor effect as the nesting variable also show significance on the score difference between pre and posttests (p-value=0.0236 for hands-on, and p-value=0.0004 for virtual) and on the posttest score only (p-value=0.0314 for hands-on, and p-value<0.0001 for virtual). These results indicate that in all modalities professor had an effect on student cognitive gains with respect to differences in pre/posttest score and posttest score only. Future will focus on qualitative analysis of features of classrooms yield high cognitive gains in undergraduate engineering students.

1. Introduction and Methods

1.1 Theoretical Framework

In the past twenty years, active learning has been increasingly used in the undergraduate classroom and results in positive student learning outcomes. Several types of implementations report success including smaller activities like minute papers or think-pair-shares [1] or course changes like in flipped classrooms [2]. Demonstrations and hands-on activities are also increasingly used in class in both virtual and face-to-face formats. With all these changes to pedagogy, we wanted to investigate whether the implementation type itself could affect student learning (such as minute papers, think-pair-share, etc.) or if the professor still heavily influences student cognitive gains which has been documented in traditional undergraduate engineering classroom instruction [3].

A helpful theoretical framework to consider this change in pedagogy is the community of inquiry. It posits a collaborative-constructivist classroom setting, whereby social presence, teaching presence, and cognitive presence are required by teacher and students to create meaningful learning experiences [4]. This framework helps to illustrate the motivation behind changing from a traditional or teacher-led classroom environment to an active learning classroom environment whereby students co-create knowledge with the teacher and their peers. In the case of this paper, we are aiming to isolate the factor of teaching presence as a variable for study. As part of the community of inquiry, this describes the design and facilitation of the classroom learning environment, aimed at fostering social and cognitive presence from student and teacher alike [5].

This work in progress study selects a specific active-learning intervention of low-cost desktop learning modules (LC-DLMs) where the learning environment or implementation sequence has been designed for use by a variety of professors. By using teaching presence in the community of inquiry as a framework, we have designed the learning experience to remain homogenous among classrooms to isolate professor effect. By professor effect, we simply mean the professor who has been assigned to teach the course (so while courses may be the same, instructors vary between these courses). To measure the effect, data on changes in student cognitive gains via pre- and posttests has been collected before and after the LC-DLM implementation. This data has then been qualitatively analyzed to investigate whether professor effect statistically significantly changes student cognitive gains.

1.2 Module Description

LC-DLMs are miniature-sized industrial engineering units that have been designed for implementation in the undergraduate engineering classroom. These modules communicate thermal-transport concepts to undergraduate engineering students. In the past, use of the modules has been shown to increase student cognitive gains [6] and the implementations incorporative active learning techniques into the classroom. Two fluid mechanics modules, the hydraulic loss as shown in Fig. 1, and the venturi meter in Fig. 2 have standpipes that operate as monometers for direct visual interpretation of the pressure head along the length of the pipe. The hydraulic loss module has a consistent diameter pipe to convey concepts of continuity and skin friction head loss, while the venturi meter has a contraction at the throat and gradual expansion to the same diameter as the incoming pipe for demonstrating fluid flow measurement principles. The standpipes are strategically placed at the entrance, contraction, throat, expansion, and end so students can observe changes in pressure along the length of the pipe. The double pipe unit shown in Fig. 2 is a heat exchanger with an inner and outer tube separated by a stainless-steel pipe, promoting the exchange of thermal energy between the two fluid streams. Several bends in the double pipe provide enough length to promote a measurable temperature change greater than 4°F (depending on the flowrate) between the hot and cold streams during a classroom experiment. For the fluid modules, the students collect flowrate and monometer head data while with the heat transfer module students record the flowrate and temperatures of the inlet and outlet streams.

Figure 1. a) Hydraulic loss (left) and b) Venturi (right) set up

Figure 2. Double pipe set up

1.3 Module Dissemination and Implementation Materials

A country-wide dissemination effort of these units has been ongoing for the past few years. Professors with different students, teaching styles, and geographic locations receive the units for implementation in their undergraduate classroom. Units are sent out every year to select faculty, who attend a summer workshop aimed at training faculty to use best practices for implementation. In this workshop, faculty become aware of all the materials available to assist in implementation and are given sessions on best classroom practices using the LCDLMs. In addition to the modules, faculty are asked to utilize worksheets that include guided experiments for students as well as homework problems that align with the pre- and posttests. The workshops faculty attend are aimed at training faculty on how to maintain fidelity to the community of inquiry teacher presence in their classrooms. Our group aims to educate all professor implementors on a similar implementation sequence and with the same materials. We emphasize the importance of implementation best practices and show data on what professors have done in past implementations that have achieved high student cognitive gains. However, to get buy-in from large numbers of faculty across the country and in an effort to respect faculty autonomy, faculty participants can modify worksheets or implementations (we encourage them not to) to best fit their pedagogical style. We do collect data about how they implemented each semester to track differences and have selected the implementations for this study with the fewest deviations from our recommendations.

1.4 Pre- and Posttests

All faculty who implement the LC-DLMs collect data on student cognitive gains before and after their implementations. This data is collected in the form of pre- and posttests, taken before and after students encounter the LCDLM. The pre- and posttests are short, 5-question or less, multiple-choice assessments about concepts regarding the most visual aspects associated with each LCDLM or concepts emphasized by the worksheets. These assessments were developed by a group of faculty familiar with the LCDLMs.

1.5 Classroom Environment Development

The homogenous classroom environment that we train faculty on has been ongoing development for nearly 15 years. The way in which these modules can be implemented has been fine-tuned based on best-practices in the literature, data collection and analysis from our group, and feedback from a variety of faculty implementors over the years. An ideal implementation would include: groups of 3-4 students with one LC-DLM, use of the worksheet provided to faculty, use of the homework problems provided to faculty, and a classroom environment where faculty engage with student groups during experimentation and discussion to keep them on task and centered on the correct concepts. We provide hardware in quantities to faculty to maintain low numbers in student groups and incorporate a few training mechanisms in the workshop to illustrate best practices. One workshop session models ideal faculty behavior during the implementation. Data is offered about why faculty should use this implementation type, linking it back to the community of inquiry and constructivism theory. While some faculty still like to modify their classroom, many maintain fidelity to the best practices we teach.

1.6 Virtual Implementations

Due to the onset of COVID-19, we had the opportunity to collect data in more than one classroom modality. Many professors were interested in continuing with the LC-DLM implementation in a virtual setting. As a result, our team developed materials to create a homogenous online classroom implementation. Materials included a series of videos available on YouTube. Videos on demonstration of each LC-DLM unit were developed, along with short concept videos that highlighted major conceptual takeaways from the worksheet. Professors who wanted to implement virtually were briefed on the best ways to use the materials for student learning. We allowed professors to implement either synchronously where all students are online simultaneously or asynchronous where students are given a time window to complete their work.

1.7 Statistical Methods and Data Analysis

Altogether data from 535 student pre- and posttest scores were collected in Fall 2020 and Spring 2021 from 14 professors doing 15 implementations using one hands-on or virtual implementation. The statistical analysis was done using JMP statistical software, version 14.0. While we considered using a Cohen’s d effect size value rather than a p-value, an effect size originates in Bayesian statistics rather than Classical statistics. Historically, the Classical statistical methodology has been favored because it is more objective, does not rely on a subjective prior distribution, and works well for larger data sets and is shown to be more robust because it follows more closely to the scientific method [7].

An ANOVA was used to assess the statistical significance of modality (hands-on or virtual) and professor effect for both the difference in scores between pre- and posttest results and the differences in posttest data. Because of the unique way data was collected in this study, it required use of both an independent variable and a nesting variable. This method, which simultaneously runs an ANOVA (which tests the independent variable) with an F-test (which tests the nesting variable) allows us to test for two changing variables: modality and professor effect. The ANOVA was used to analyze the variance within the groups to determine statistical significance and the f-test was used to determine whether professor within each group had an effect. A MANOVA was not appropriate in this case because the only dependent variable was student scores. Had professor been a dependent variable then a MANOVA would have been used.

In the statistical analysis, we ran a total of three types of tests. The first was an ANOVA where the independent variable is professor effect. In this case, we combined modalities of virtual and hands-on and only used professor effect as a variable. Statistical significance from this test would indicate that regardless of implementation modality the professor assigned to the course had an effect on student cognitive gains. We used two separate dependent variables: the difference in pre-posttest scores between classrooms and the difference in posttest scores only between classrooms. The two dependent variables aim to answer the question whether prior knowledge affected the outcome.

The other two tests included both an independent variable tested with an ANOVA and a nesting variable tested with an F-test. These are noted as F-tests in the results section. The first of these two had the virtual modality as the independent variable and professor effect as the nesting variable. The second used the hands-on modality as the independent variable and professor effect as the nesting variable. Statistical significance from these tests indicates that both the independent and nesting variables create an effect on the dependent variable. Again, we ran two of each with different dependent variables the same as those for the ANOVA without the F-test.

Finally, to ensure these tests are valid normality of the data set must be confirmed within the results. This ensures the assumptions of the test are valid for the given data set. To ensure normality, a Q-Q plot was generated for both the differences in pre-test scores and posttest scores.

2. Results and Discussion

2.1 Confirmation of Normality

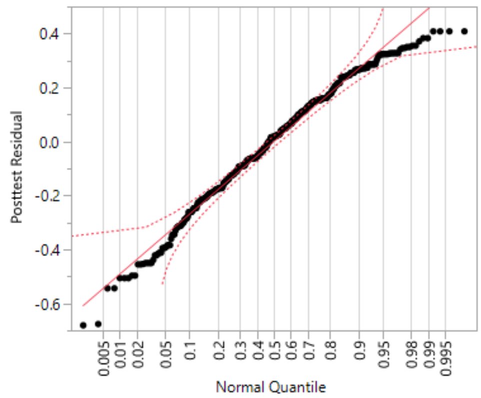

Figure 1. Q-Q plot of Posttest scores.

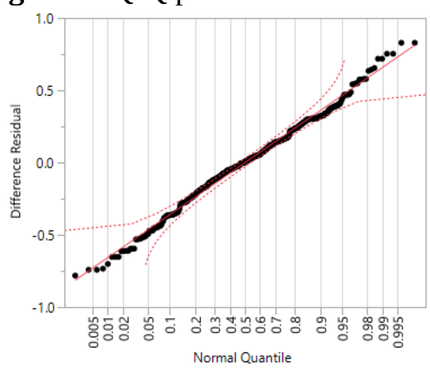

Figure 2. Q-Q plot of difference in scores results.

The two graphs shown in Fig. 1 and Fig. 2 are Q-Q plots that confirm normality. It is clear these are normal because all data points fall within the normal range, as illustrated by the data points falling within the boundary shown by the dotted lines. Because the data is confirmed to be normal, we can run an ANOVA and an f-test on this data set.

2.2 Dependent Variable Analysis

Before examining the results of the statistical tests, a preliminary analysis on the two dependent variables was done. The results from the two analyses can be seen in Figs. 3 and 4. Fig. 3 illustrates the differences in both variance and mean between the pre and posttest score differences for all 15 implementations. Fig. 3 also illustrates the differences between student cognitive pre/posttest performance between the modalities of virtual and hands-on. Fig. 4 illustrates the differences in posttest data only between the 15 implementations and between the hands-on and virtual modalities. The figures illustrate differences in mean between professors and differences in the highest and lowest student performances in implementations. A key difference between Figs. 3 and 4 is when considering pre/posttest data, many students performed worse on the posttest than the pretest (as indicated by a difference less than 0). However, since the posttest data is simply the average, this comparison to baseline is not captured.

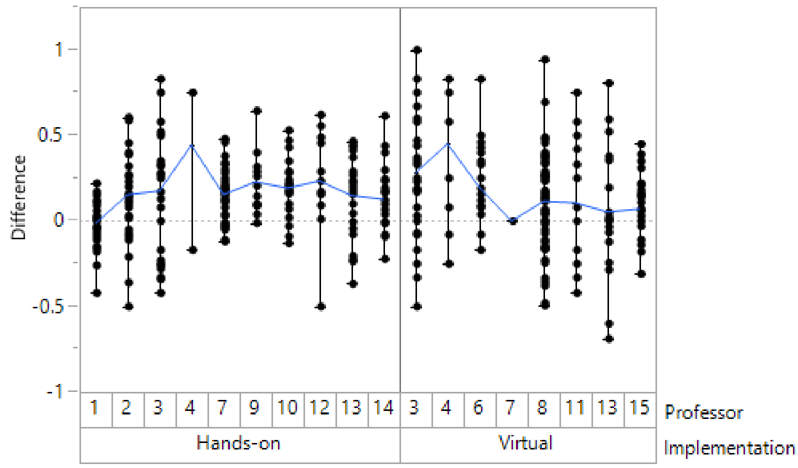

Figure 3. Variability graph showing the difference between pre- and posttest scores for each professor.

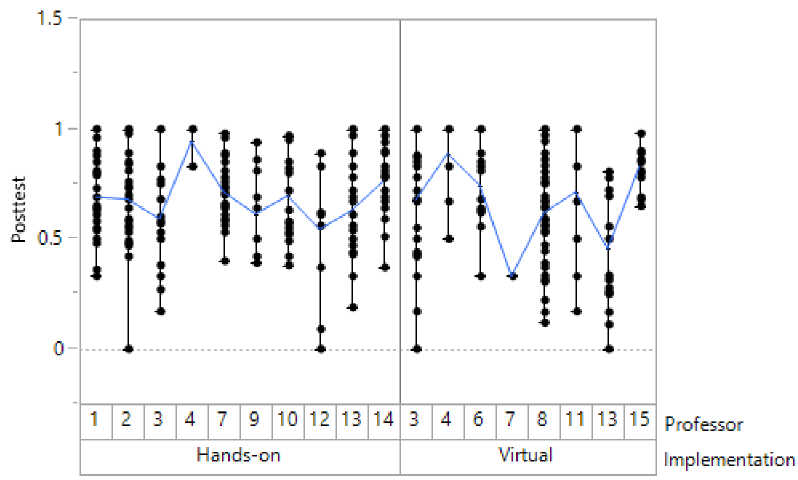

Figure 4. Variability graph showing the posttest results for each professor within each implementation

2.3 ANOVA on Overall Results

An ANOVA without an F-test using only professor effect as an independent variable was run using both the score differences in pre/postest data and the score differences in posttest data. Results from the ANOVA can be seen in Table 1. Since p-values less than 0.05 are observed for both the ANOVA tests, we can conclude that regardless of modality professor had an effect on student cognitive gains with respect to both dependent variables. This result is not that surprising especially when taken in the context of teacher presence within the community of inquiry. Significance may have appeared because the modality in this case was held constant, and the training for the virtual and hands-on implementations was different between professors. This result indicates that when considering the LC-DLMs as a stand-alone intervention, they do not facilitate student learning without the aid of the professor. The next step is to divide modalities and test significance of professor effect when teaching presence has been specifically designed to be homogenous.

Table 1. Results of ANOVA for difference in pre- and posttest scores and posttest scores.

Implementation	P-value
Difference	<0.0001
Posttest	0.0004

2.4 ANOVA and F-Test Results

An ANOVA with an F-test was run on the score difference between pre/posttest results with the independent variable as modality and the nesting variable professor within implementation type. As seen in Table 2, each of these tests are significant (p-value=0.0236 for hands-on, and p-value=0.0004 for virtual), indicating that even with holding the modality constant, professor has an effect on score change in pre/posttest scores. This finding shows that the LC-DLM implementation and subsequent effect on cognitive gains between professors with similar reported methodology still depends on the professor. Before considering the implications of this result further, it is important to consider the result from the final test.

Table 2. Results of ANOVA and F-test for difference in pre- and posttest scores

Implementation	P-value
Hands-on (F-Test)	0.0236
Virtual (F-Test)	0.0004

The third test we ran was an ANOVA with an F-test using posttest score as the dependent variable. This test also resulted in significance for both the hands-on and virtual modalities (p-value=0.0314 for hands-on, and p-value<0.0001 for virtual). This further indicates that regardless of hands-on or virtual implementation, the professor impacts student learning. Because this test only examined posttest data, it implies that the prior knowledge of students entering the class also did not have an effect on cognitive gains. Taken together, the results from both ANOVA with F-tests indicate that the effect of professor is significant in both modalities. The difference in pre- posttest scores and the raw posttest scores follow the same trend, showing a student's professor significantly affects their cognitive understanding on concepts associated with the LCDLMs.

Table 3. Results of ANOVA and F-test for posttest scores

Implementation	P-value
Hands-on (F-Test)	0.0314
Virtual (F-Test)	<0.0001

The results of the ANOVA and F-tests are surprising especially when taken in the context of teacher presence within the community of inquiry. If anything, of all the tests these should not have been significant because the training for the virtual and hands-on implementations was different between professors. This result shows that the trainings we offer to faculty participants might have lower implementation fidelity than we hope to achieve with the workshops. The result may have significant implications for how the trainings are run and highlights the importance of further understanding what features of teacher presence in the classroom truly affect the community of inquiry whereby students co-construct meaning from the LC-DLMs, worksheets, and their peers.

To better understand the causes leading to the results seen, we will transition from a quantitative analysis to a qualitative analysis. The initial quantitative step aimed at investigating whether significance existed between professors using the LC-DLMs. Now that evidence is clear it does, we will need to further investigate how and what professors do in the classroom to facilitate a community of inquiry whereby students can collaboratively co-construct knowledge. Finally, investigating professor's perceptions of the LC-DLMs and whether their satisfaction with the hardware and worksheets influences student learning would also be beneficial.

3. Conclusions

In this study, we simultaneously investigated the modality of hands-on or virtual environment and professor effect using LC-DLMs, collecting data on student cognitive gains as a result of this intervention. Framed using the community of inquiry, professors were trained on how to best implement the modules in the classrooms, with the learning environment designed for them. Three statistical tests were run to determine if professor had an effect on student cognitive gains: a single ANOVA combining modality and testing for professor effect only, an ANOVA with an F-test dividing modality between hands-on and virtual and testing individual professor effect on pre/posttest differences and a third ANOVA with F-test where the dependent variable changes to posttest cognitive data only. Each of the tests yielded significance in every domain, indicating professor had an effect when modality mattered (hands-on or virtual) and professor had an effect when modality didn't matter. Because we aimed to train professors to create a homogenous learning environment, these findings are significant because the trainings may not be providing as uniform a message as we hope. Future work will include further investigation into features of a classroom that yield high cognitive gains via qualitative rather than quantitative analysis.

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