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2025 ASEE Annual Conference & Exposition
Palais des congrès de Montréal, Montréal, QC • June 22–25, 2025
Paper ID #47273

BOARD # 291: Progress in Evaluating Hands-on Learning Module Implementation and Considerations of Social Cognitive Theory

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Progress in Evaluating Hands-on Learning Module Implementation and Considerations of Social Cognitive Theory

Introduction

Over the past seven years, our team has disseminated low-cost hands-on learning hardware and associated worksheets in fluid mechanics and heat transfer to provide engineering students with an interactive learning experience. Previous studies have shown (1-5) the efficacy of teaching students with an active learning approach versus a more traditional lecture setup, with a number of approaches already available, such as simple active discussion, think-pair-share, flipped classrooms, etc. Our approach is differentiated by the inclusion of hardware to add both a visual aid and an opportunity for hands-on experimentation while keep the costs low enough for a classroom setting. Learning with a hands-on, interactive approach is supported by social cognitive theory (SCT) (6-8) and information processing theory (8). Unlike earlier views of learning theory, which simply posit that the key to learning is repetition, social cognitive theory considers the agency of the student and the social aspects of learning. The primary assumption of SCT is that students are active participants in the learning process, acquiring and displaying knowledge, skills, and behaviors that align with their goals through a process called triadic reciprocal causation, illustrated in figure 1.

In this process, according to SCT, the three factors to consider are the students' goals and values, their behavior (in this case an indicator of their knowledge) and their environment, which includes not only the classroom and their available tools, but student peers and their instructors. Through group activities using the hardware we have dubbed desktop learning modules, or DLMs, students will not only learn directly by interacting with the module but also by observing others and discussing their conclusions. This allows adjustments to be made to the students' understanding of the module much more quickly and efficiently than if they were studying and formulating these conclusions without an outside reference.

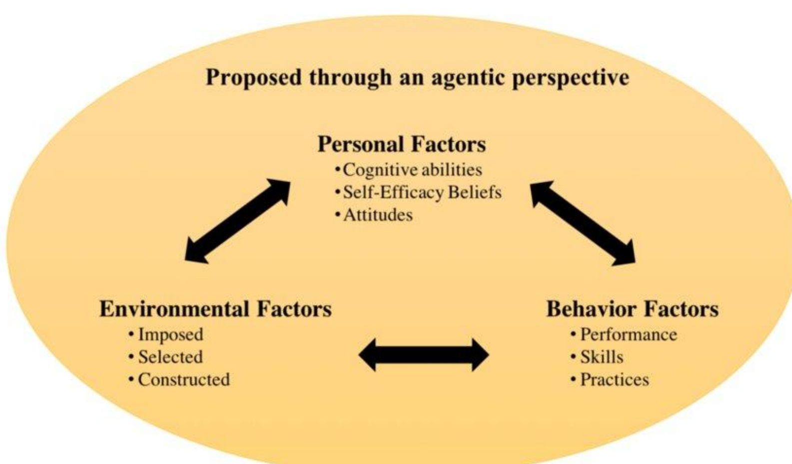

Fig. 1. Graphic of Bandura's triadic reciprocal causation, with the various factors broken down into subcategories. Notably, he made the distinction between imposed and selected factors in one's environment to emphasize the

amount of control the person learning has during the process and stressed the importance of personal agency in the personal category, as stated by Verdin and Godwin(9). Constructed factors are a middle ground, such as school projects where students are required to participate but employ several personal agencies in completing the task.

The other theory supporting our approach is information processing theory (10), which is used to describe the process by which knowledge is moved from short-term or working memory to long-term memory, and how that information is recalled by an individual later. The primary assumption behind Information Processing Theory is that every lesson, whether it be information, a skill, etc., that a student learns has some Cognitive Load associated with it. When simplified to its most basic components, every lesson has some intrinsic load a student must overcome for the lesson to be considered "fully learned", with more complex topics having more intrinsic load, such as engineering topics requiring a foundation in science and mathematics before they can be comprehended. In addition to this, however, lessons often have extra or "extraneous" load, which refers to the cognitive load a student takes on to organize new and unfamiliar knowledge. Thus, an ideal lesson plan would limit extraneous load as much as possible by organizing and dividing its material. Knowledge that has been learned in an organized fashion is also easier for the student to recall later, as it is more interconnected with other information (11). Physical models can help reduce the extraneous load of having to visualize phenomena from a text description or two-dimensional illustration.

Currently, there are four main Low-Cost Desktop Learning Modules, or LCDLMs in circulation, two for fluid mechanics and momentum transfer, and two for heat transfer, all of which are displayed in photos in Fig. 2. In the first set, we have an LCDLM meant for modeling hydraulic pressure loss by showing a series of manometers along a horizontal pipe. The manometers serve to assist in visualizing the correlation between pipe length, pressure change, and change in velocity for an incompressible fluid (water). The second in the fluid mechanics kit is a miniature Venturi meter, which is used to display the transformation of mechanical energies for an incompressible fluid due to changing pipe diameters, from flow work to kinetic energy and back, along with the energy loss due to viscous forces. The last two, which are part of the heat transfer kit, include a shell and tube and a double pipe heat exchanger, which cover the basic principles of heat exchange (conduction and convection) while also showing different configurations so students can learn about the effects of parallel, cross, and counter flow on heat transfer rate.

Additionally, we have two other LCDLMs which have only been used at our university due to limited production: The fluidized bed columns and the evaporative cooler. The first is meant to model the pressure trends associated with fluidization using a bed of beads. The second is meant to teach students about how air velocity, humidity, and phase changes affect heat transport.

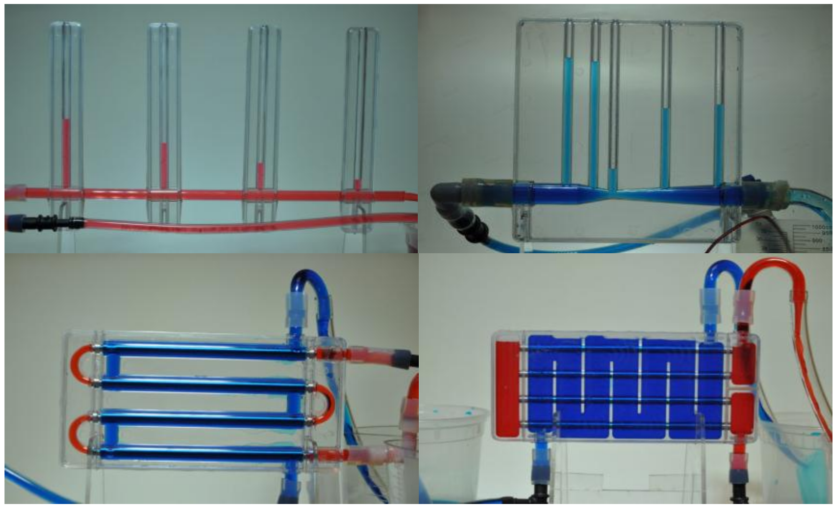

Fig. 2. The four main DLMs in circulation. In the upper left is a horizontal pipe showcasing hydraulic loss, upper right a venturi meter, the lower left a double pipe heat exchanger, and the lower right a shell and tube heat exchanger.

Dissemination

During the initial dissemination process, we followed a "Hub and Spoke" approach. In 2018, several regional hubs were set up across the United States, where professors and other staff who agreed to participate in the first year of the study would first be given instruction to use and implement the LCDLMs in the classroom and collect data from their students. They would in turn provide support to universities in their regional areas who agreed to come aboard later by providing them with guidance and support outside of the workshops we provided, thus promoting LCDLM usage. Training workshops were held on a yearly basis at these locations to provide updated information and modules for new implementors who were invited by previous participants. However, after the pandemic, changes were needed due to health and safety concerns. Around 2021, training workshops were held by videoconference over Zoom, where the opportunity was also taken to begin disseminating information on institutional performance year-by-year. Recordings of these online workshops would then be used as a form of orientation for new participants in the study as the project began to expand in scale. By 2024, the focus had shifted from gathering new participants for the study to analyzing the data already available and continuing to support previous participants.

Feedback Discussion

Five years into the study, the data we collected demonstrated the efficacy of the active learning approach through student performance. When analyzed, yearly student performance and as shown in Fig. 3 results show significant improvements in the topics relevant to the DLMs based on the results from their pre- and posttests. However, results between institutions and implementations also showed differences in performance, both in terms of the amount students would improve in their final test results. To address this and further improve the DLMs going forward, we plan to use the remainder of the study to identify, disseminate, and test more effective strategies in the usage of DLMs in the classroom.

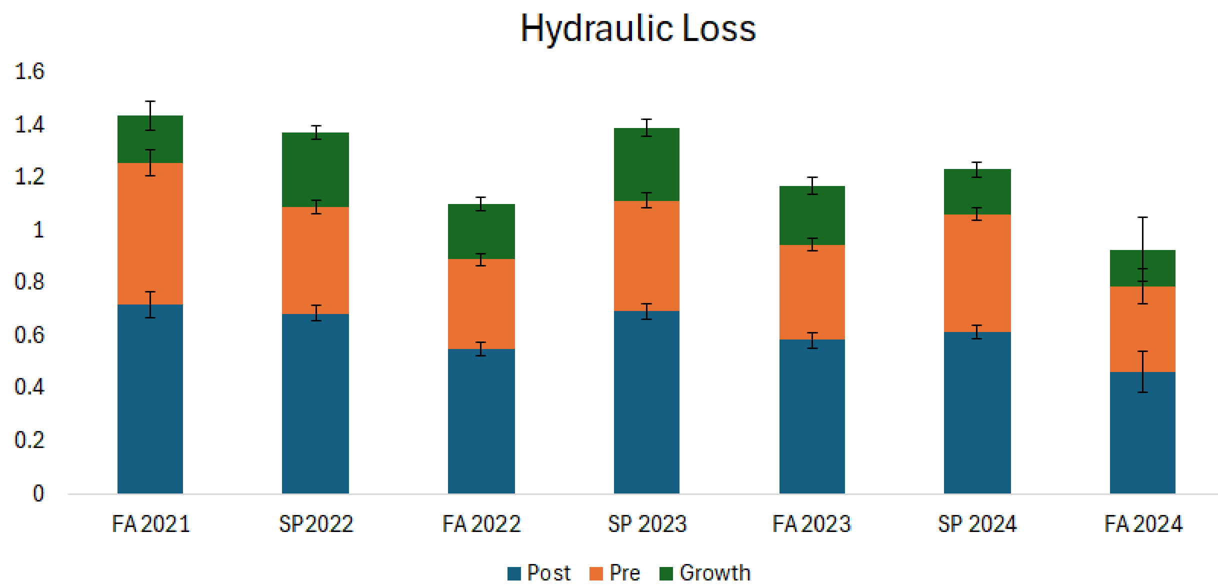

Fig. 3. Sample of pre- and posttest results, comparing relative scores and growth overall across different semesters from Fall 2021 to last semester, as of this writing.

After reorganizing the data, we conducted an analysis and identified the best performing classes and institutions amongst the 22 universities and 33 professors who participated since fall semester 2019 and matched them with the observations and procedures they have submitted alongside their results. In addition to the workshops, the faculty who implemented and submitted their student test results were encouraged to provide both their feedback on the DLMs, reporting on their effectiveness, any malfunctions, and a description of their implementation procedures. It was through this initial meta-analysis that we found a few patterns, which were compiled into a first draft of a "best practices" document.

To briefly summarize the "best practices" document, we urged implementors to follow a specific timetable for implementation, shown in the Fig. 4 below. One of the patterns that appeared in the best performing institutions was the amount of time allocated for students to take the posttest examination after using the LCDLMs. Those who had students take the exam within 1-2 days tended to perform better in terms of growth, compared to instructors who gave their students a full week or tested students within the same class period. In the former case, this performance issue is likely due to a lack of relevance. At that point, students will have moved to a different topic in the class period, so the results from the lab would be harder for students to recall. In the latter case, rushing students through the exam prevents discussion of the topics or engagement with the material in an in-depth manner.

Aside from the timetable, we also requested professors assign homework for students to complete prior to taking the posttest, which we provided in the form of a worksheet and online tutorial video content. The higher performing institutions typically had some form of homework assigned after the LCDLM session, but usage of the worksheet we provided was inconsistent, with professors instead using an edited version or assigning their own assignments to align with their schedule and lecture material, such as requiring a lab report on the LCDLM session in the place of homework.

	Class period (0 = LCDLM day)								
Tasks	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**
1. Lecture on Principles	■	■	■	■					
2. Preparation for LCDLM	■	■	■	■					
• **Consent Form & Pre-Test (5–7 min) – 5 pts† for completing these**		■	■	■					
• Instructor & TA: practice LCDLM while going through worksheet		■	■	■					
• Instructor & TA: Charge batteries & watch implementation video				■					
• Show students the set-up videos & assign relevant readings				■					
3. LCDLM Implementation & Worksheet					■				
4. Days after LCDLM Implementation						■	■		
• Assign LCDLM **Tutorial Videos** & completing of worksheet/homework						■	■		
• Collect worksheet & associated homework (one per team)						■	■		
• Posttest *in-class* after worksheet/homework submission • 10 pts†: Incentivizes best work							■		
• Students take motivational survey by midnight – 5 pts† for completing							■		
5. Instructor & TA: Complete Post-Implementation Form						■	■	■	■

Fig. 4. Gantt chart for LCDLM implementation. †Professors were allowed to adjust points to be consistent with their grading policies.

Participant Interviews

Last year, professors and graduate students who had previously implemented the DLMs in their classes were invited to a short interview over Zoom to provide us with additional information on their implementation process. Emphasis was placed on participants who had implemented multiple years in a row, and who had sent us data between Fall 2023 and Spring 2024, when the first draft of our best practices document went into circulation. Up until this point most feedback was provided via the post-implementation survey mentioned above, which professors were asked to complete at the end of the semester. However, most professors kept their descriptions concise or didn't respond at all questions due to a lack of time or incentive. The purpose of the interviews was to receive a more detailed description from participants of their implementation strategies, how they evolved over time, and any contributions they may want to make to our best practices.

A common miscommunication we identified was that participants were not using our web-based resources during implementation. During the pandemic, participants had asked for a virtual alternative to the LCDLMs to provide students with a similar learning experience during the lockdown and to continue sending in data. To meet this end, our team filmed and released several videos onto YouTube breaking down the LCDLMs in greater detail, along with several demo videos directly on our website to show how the LCDLMs are supposed to be assembled. Unfortunately, we failed to provide a link to the YouTube channel in our best practices document, and navigating to it via our website proved challenging unless participants knew what to look for. As a result, many participants did not use the supplemental videos as instructed.

Future Work

Fluidized Bed Reactor

Fluidization refers to the suspension of solids into a fluid-like state when subjected to a current of gas or liquid at a specific velocity. The resulting fluidized state enhances contact between the surface of solid particles and reactants in a solution, leading to heightened reaction rates and improved process efficiency. Understanding this dynamic system is non-intuitive, making it ideal for an active learning approach. While we have already implemented a simple fluidized bed for the purpose of exploring the pressure trends associated with fluidization, recently, we have also incorporated a chemical reaction into a new version of the LCDLM by immobilizing the lactase enzyme in alginate beads. The immobilized lactase catalyzes the conversion of lactose substrate in the solution flowing through the bed into glucose and galactose. A colorimetric assay is used to track the progress of the reaction. Trials were conducted in a unit operations lab course during the Fall 2024and Spring 2025 semesters, with learning gains being monitored.

Glucose Analyzer

Lastly, further expanding into the realm of chemistry, the newest LCDLM we are preparing for classroom implementation is a glucose spectroscopic analyzer which uses a cellphone as the primary sensor for taking measurements. The purpose of this LCDLM is to provide chemical engineering students with a practical example of spectroscopy, stoichiometry, and microfluidics to supplement a fourth-year class on kinetics and reaction engineering. Thus far, both the proof-of-concept and the current version of the module have shown promise in a controlled setting, however a full procedure for classroom implementation still needs to be developed and revised before it can be properly evaluated as a learning tool.

Currently, we are in the process of fabricating enough modules for a beta test, which will be conducted by a group of undergraduate students tasked with constructing a viable calibration curve as well as determining the concentration of glucose in an unknown solution. From there, assessment questions will be developed for a pre- and posttest, such that the efficacy of the module can be supported by data on a similar scale to prior LCDLMs.

Acknowledgements:

We acknowledge NSF support through IUSE #1821578 and 1821679

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