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NSF IUSE: Progress in Evaluating Hands-on Learning Module Implementation with a Social Cognitive Lens and Alternative Web-based Experiments

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Prof. Bernard J. Van Wie received his B.S., M.S. and Ph.D., and did his postdoctoral work at the University of Oklahoma where he also taught as a visiting lecturer. He has been on the Washington State University (WSU) faculty for 41 years and for the past 27 years has focused much of his effort on developing, implementing, assessing and propagating use of hands-on modules and interactive exercises that can be used in standard lecture classrooms so students do not need to wait till their senior year to see examples of process equipment. He also leads a strong program in bioreactor design for biomanufacturing of cartilage tissue and cells for immunotherapy.

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John L. Falconer is the Mel and Virginia Clark Professor Emeritus of Chemical and Biological Engineering and a President's Teaching Scholar at the University of Colorado Boulder. He has taught courses in thermodynamics, kinetics/reaction engineering, and catalysis. His research is in the areas of zeolite membranes and heterogeneous catalysis. He has directed the effort at the University of Colorado Boulder to create learning resources on www.LearnChemE.com and he is responsible for maintaining the Teaching Resource Center on the CACHE website (https://cache.org/teaching-resources-center). He has received the AIChE Warren K. Lewis Award for Chemical Engineering Education, the ASEE CHED Lifetime Achievement Award, the Edgar CACHE Award in chemical engineering education, and the AIChE Himmelblau award.

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Professor Dutta joined the School of Mechanical and Materials Engineering of Washington State University (WSU) in 2001, where he has been a tenured Full Professor since 2013. During his sabbatical years, he worked as a Visiting Professor at Konkuk University, Seoul, South Korea and the Technical University of Darmstadt, Germany. His primary research area is Micro, Nano, and Biofluidics with a specific focus on the development of new algorithms for multiscale and multiphysics problems. Lately, he developed a suite of physics-based machine learning models for heat and mass transfer problems. He has published more than 200 peer-reviewed journal and conference articles. Prof. Dutta organized and chaired numerous sessions, fora, symposia, and tracks for several ASME (American Society of Mechanical Engineers) and APS (American Physical Society) conferences and served as the Chair of the ASME Micro/Nano Fluid Dynamics Technical Committee. Moreover, he served as an Associate Editor for the ASME Journal of Fluids Engineering; currently, he is an Editor for Electrophoresis. Prof. Dutta is an elected Fellow of ASME, and he is a recipient of the prestigious Fulbright Professorship sponsored by the US Department of State.

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Md Shariful Islam is a PhD candidate in Mechanical Engineering at Washington State University, Pullman. He completed both Bachelor of Science and Master of Science in Mechanical Engineering from Bangladesh University of Engineering and Technology (BUET), Bangladesh. He is also working as a trainee of the NRT-LEAD program funded by NSF. His research interests include engineering education, Desktop learning module for STEM education, Machine learning-assisted inverse heat transfer problems, and computational modeling of thermal ablation. In addition to academic pursuits, he served as the president of the NRT Student Club (NSC) at WSU, where he led initiatives to foster interdisciplinary collaboration, professional development, and student engagement in STEM research.

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Ankur Gupta, PhD, is an Assistant Professor of Chemical and Biological Engineering at the University of Colorado Boulder, with affiliated appointments in Applied Mathematics and Materials Science and Engineering. His research focuses on transport phenomena in electrochemical and soft-matter systems, with applications to energy storage, separations, and active colloids. He teaches the transport phenomena course for chemical engineering PhDs. He earned his PhD in Chemical Engineering from MIT.

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Introduction

Over the course of an eight-year period, our team has promoted the use of interactive, hands-on learning in the engineering classroom through the dissemination of low-cost desktop learning modules, or LCDLMs (1-2). Studies have shown that an active learning approach can increase student knowledge retention and engagement (3-6), but there exist multiple approaches to active learning that do not require hardware. While the use of learning tools comes with additional costs, the benefits of a hands-on approach include not only visual and tactile cues but also an opportunity to leverage the social aspects of learning posited by Albert Bandura's Social Cognitive Theory (7-8).

Under Bandura's framework, and most cognitive frameworks for student learning, learning can come from two source categories: enactive or vicarious (9). Enactive learning occurs when students practice the skill or behavior they are trying to learn. Vicarious learning occurs when students learn from a model, such as a diagram, a text, a video, or even another individual performing the action. A hands-on approach provides ample opportunities for both types of learning which provide different benefits. Enactive learning is better for reinforcement of existing assumptions or the detection of contradictions, while vicarious learning is better for introspection since it provides a different perspective.

Social cognitive theory also states that learners are not passive during the learning process (9). Learning according to most learning theories is defined as a permanent change in outward behaviors, which includes skills, attitudes, and performance. Since students are free agents, their behavior is dependent on their personal factors, such as their personality, preferences, and goals, and their environment, which includes not only their surroundings but also their peers and mentors. By having their peers serve as a model for vicarious learning, students will learn with greater motivation and engagement than if they were working independently with a video or diagram, since they will be operating with external social pressures acting on them, judgement, validation, comradery, etc.

Dissemination & Implementation

There are currently four LCDLMs available to other universities, each covering a different topic in chemical engineering (10-11). To become a part of the study, professors at other universities needed to be instructors in a relevant course, specifically heat exchange or fluid mechanics. Up until 2020, participants were trained in person at localized hubs, with hub coordinators receiving training on how to use the LCDLMs before assisting in passing this information along with the LCDLMs to the other participants. During the pandemic, we transitioned to a remote model to accommodate the distancing restrictions. We chose to stick with this model for its convenience as the project's primary data collection period began to wind down. In 2023, we stopped providing financial stipends to participants due to the initial grant reaching its end point and shifted focus away from finding new participants to supporting those who continued using the LCDLMs. Participants have expressed an interest in continuing to use the LCDLMs and send in their students' academic results, and as of writing, our team is the only way for them to replace broken or missing components.

During implementation, student learning is evaluated using a set of assessments, one taken prior to using the LCDLMs to establish their knowledge base, and one taken after to assess how much their knowledge has improved. They are also given a survey to fill out detailing their experience with the LCDLMs. The survey is used to ask questions such as whether LCDLMs clearly illustrate the phenomenon and whether they were engaged in the activity or simply going through the motions. Afterwards, we also collect data on the professor's implementation procedure by having them fill out a survey as well.

In late 2022 to early 2023, we sought to close the disparity in learning and engagement outcomes between institutions by providing study participants with a set of guidelines we referred to as our "best practices" document. This document was based on the strategies employed by the top performing implementers amongst our participants, and our hypothesis was that an optimal implementation strategy could be identified. The document primarily details a schedule for an LCDLM implementation, what material to lecture on prior to the pre-assessment and prior to implementation, and activities student should complete after implementation. To provide an example, Engineering Teachers implementing a fluid mechanics module (either Venturi meter or horizontal pipe) would provide students with lecture material on the mechanical energy balance equation 3-4 days prior to implementation and before any student assessments are taken. They were, however, barred from lecturing on the module specifically, such as what a Venturi meter is for and how to apply the mechanical energy balance to it.

We have also provided faculty with additional materials required in the Best Practices aside from the LCDLMs, including homework and web-based materials. Since Fall of 2024, faculty following the best practices have students complete some form of homework and interact with the web-based materials prior to taking the posttest on the activity. This allows students more time to contemplate what they learned. Thus far, the implementation of a more uniform approach with these guidelines serving as a framework has produced a statistically significant improvement in assessment results based on a two tailed t-test (see figure below), but further investigation is warranted due to the size and variation of the data set.

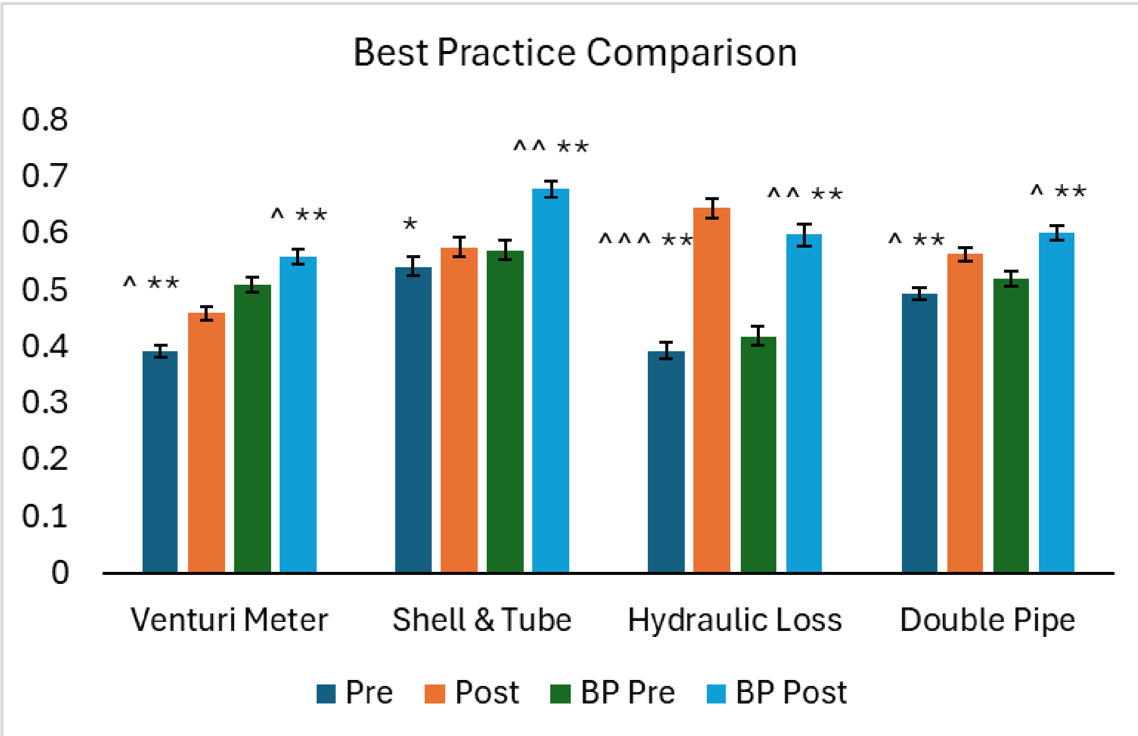

Figure 1. Overview of student test results prior to (pre and post) and after (BP Pre and BP post) implementation of our best practice guidelines. A double asterisk (**) indicates a p-value of less than 0.01, suggesting a rejection of the null hypothesis, while a caret (^) indicates a Cohens D value greater than 0.2, suggesting a small to medium effect size. See table for exact values.

	Venturi Meter	*Shell & Tube*	*Hydraulic Loss*	*Double Pipe*
Pre	0.39	0.54	0.39	0.50
Post	0.46	0.58	0.65	0.57
BP Pre	0.51	0.57	0.42	0.52
BP Post	0.56	0.68	0.60	0.60
Cohen's D	0.35	0.16	0.82	0.36
P-value	9.42E-09	0.027	1.29E-46	5.49E-12
Cohen's D, BP	0.31	0.51	0.57	0.39
P-value, BP	8.05E-04	4.4E-10	1.34E-15	2.52E-08

Future Work

Our team's future work will focus on two parallel efforts. The first is the continued development of two new LCDLMs that expand our work into biochemical reaction and measurement. The second is an ongoing collaboration with the University of Colorado Boulder to develop simulated versions of our LCDLMs and compare the learning outcomes produced by a hands-on approach versus a virtual approach.

For biochemistry development, we developed a fluidized bed reactor with enzyme beads that can be used to demonstrate reaction engineering concepts in a classroom setting. In particular, this module will be used to illustrate how reaction rates depend on kinetic parameters and how the observed reaction behavior can be affected by transfer-related limitations. The second module for biochemistry in development is the glucose analyzer, which is intended to provide students with a rudimentary set up with which to perform spectroscopy experiments.

Finally, our collaboration with the University of Colorado Boulder will continue as their team develops simulation-based versions of our LCDLM activities. The purpose of this effort is to compare a hands-on approach, where students interact directly with physical modules, to a virtual approach, where students engage with simulated versions of the same phenomena. We have begun this comparison using modules and topics, including hydraulic loss, the Venturi meter, and the heat exchangers. Future work will expand this effort by increasing the number of implementations and analyzing the data to determine whether there are statistically meaningful differences in student learning and engagement between the two approaches. Emphasis will also be placed on student preferences and pinpointing strengths and weaknesses in the two approaches students explicitly identify, such as difficulties with data collection or examining geometry. Our thought process being to identify which activities warrant a physical demonstration or activity over a virtual one with measurable data.

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