AC 2011-816: ONLINE FINITE ELEMENT TUTORIALS AS ACTIVE LEARNING TOOLS

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Selected publications Integrating Fatigue Analysis into Machine Design Course or Finite Element Course


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Abstract

Engaging in active learning promotes deep conceptual understanding and possibilities to cultivate valuable aptitudes for synthesizing, analyzing, and evaluating ideas and creating new ones. Over the last few decades, a plethora of research supporting active learning pedagogy indicates that this approach to learning needs to be incorporated in teaching. Multiple literacy practices, participating in discussions, hands-on activities, collaborative learning, and real world problem solving are among the many ways to facilitate active learning. The skills acquired during active learning tend to go above and beyond basic comprehension of information covered during a lecture. In fact, the goal of active learning is to not only develop student comprehension, but also to a) increase the learner’s investment, motivation, and performance, b) empower the learner to make real world connections, c) promote independent, critical, and creative thinking, and d) facilitate collaboration. One model for active learning takes the form of tutorials, or more accurately described as active learning modules (ALMs), aimed at improving student learning in historically difficult subject areas in engineering through the application of finite element analysis. The tutorial set developed here includes learning modules for various subject areas in Mechanical, Electrical, and Biomedical Engineering courses. The purpose of this study is to determine if ALMs of this type are effective active learning tools. In each participating course, after the student completes their traditional lecture series, they are introduced to a computer-based ALM. In order to perform a baseline study, students are administered content quizzes before and after the completion of the module. These quiz results are statistically analyzed to determine if subject aptitude, including comprehension, is improved. The incorporation of a novel assessment methodology reinforces the project goals as we are able to evaluate if these modules afford all students, regardless of learning style or personality type, with an equitable active learning process experience. The ALMs are shown to be a successful step towards improving aptitude and comprehension of challenging engineering content in an active learning environment.
**Introduction**

In the quest to improve engineering education, the active learning methods must be designed, assessed, and implemented effectively. Even though active learning is frequently used in other disciplines, these pedagogical techniques have not yet been fully developed in engineering curriculum, especially within core courses [1-3]. For this current work, we consider active learning to be anything that goes beyond the traditional model of students passively listening to a lecture. Hands-on activities, problem based learning, interactive software and collaborative learning are all specific pedagogical techniques that are integrated into our learning module-based active learning repertoire in order to enhance students’ experiences in engineering education. Such active learning approaches have the potential to improve student comprehension and knowledge retention and, also, to increase students’ interest in the material [4]. The main goal in this current work is to present the design, development, and assessment of one type of active learning tool, i.e. finite element (FE) learning modules. These Active Learning Modules (ALMs) fit in the general category of problem based learning [5,6]. Effectiveness of these ALMs is assessed based on improvement in student performance in general coupled with equitability of learning enhancement across a variety of student demographic groups.

Twelve ALMs were designed based on active learning pedagogical research and were then evaluated in various classroom settings. Traditional lectures in selected engineering courses in the Mechanical, Electrical and Biomedical Engineering fields of study were supplemented with these ALMs. Two overall project goals drive the details of the design, implementation and assessment of the ALMs. These overall project goals are:

1. Use the ALMs to provide a method to enhance students’ understanding of conceptually difficult engineering concepts,
2. Use the ALMs to provide a baseline exposure to the finite element (FE) method of engineering analysis.

The following process is used to implement and assess the ALMs. Participating students are given a quiz to evaluate their baseline understanding of historically difficult engineering topics. This is labeled the “pre-quiz”. Then the FE-based ALMs are administered and the same quiz retaken. This is called the post-quiz. This procedure is used, from a holistic viewpoint, to assess if these ALMs are accomplishing the goal of improving student learning.
Noting that the quizzes are designed to evaluate students’ ability to accomplish specific learning objectives, the effectiveness of the ALMs is measured by the increase in post-quiz (taken after the ALM) scores over pre-quiz (taken before the ALM) scores. Additionally, improvements in quiz scores are correlated to learning styles, personality types and other demographic variables, followed by the application of basic statistical analysis. The end goal is to assess the effectiveness of the ALMs in two specific manners. First, the general effectiveness of the ALMs is measured by considering the overall improvement of the students’ post-quiz scores over their pre-quiz scores. Second, quiz improvements are categorized based on demographic variables and the improvement levels of different demographic groups are compared. This second assessment technique involves correlation studies between quiz performance and student demographic type which provides understanding of whether the enhancement from the ALMs is equitable across these different demographic groups. These two assessment procedures lead to two project assessment objectives:

1. **Determine the overall effectiveness of the ALMs.** This is primarily based on the delta between the pre-quiz and the post-quiz.

2. **Determine the effectiveness of the ALMs across different demographic groups.** This is primarily based on the quiz deltas of the different demographic groups.

This paper presents the overall results of the implementation and assessment of twelve FE modules. To provide context for this work, active learning approaches are reviewed in a following section. The literature review reports an overview of the research to date in active learning and provides some details on state-of-the-art active learning aspects that are particularly applicable to our work. Our FE analysis learning modules are seen in this context to be viable active learning tool. After the active learning literature review, the focus of this work will shift to our assessment approach. The innovative assessment/demographic type correlation method is discussed below and in even greater detail in the precursor to this work [7, 8]. Our assessment focus, in this current work, will delve into the specific demographic correlation results as well as the global results of the ALMs as a whole. After the results portion, possible improvements to the learning modules are discussed, focusing on how the ALMs may be iteratively refined and implemented as improved active learning tools.
Active Learning Approaches

Once the ALMs have been created, their effectiveness in enhancing learning is assessed in a closed-loop fashion using the Felder-Soloman Index of Learning Styles (ILS) and the Myers Brigg Type Indicator (MBTI). Specifically, the students’ pre- and post-ALM quiz scores are grouped according to their ILS and MBTI data. If one student group is determined, from their pre- and post-ALM quiz scores, to benefit more from the ALM than a different group, the ALM can be modified accordingly. For example, if the MBTI-introverts are found to benefit more from the ALM than the MBTI-extroverts, then additional collaborative learning (which tends to energize the extroverts) could be added to the ALM. The two pedagogical background theories (ILS, MBTI) used to develop this work are not unique to this research, but combining their foundations to design and assess these ALMs is an original effort. Because ILS and MBTI are likely familiar to the reader, they are not described in detail here. However, details can be found at [p] for ILS and [10] for the MBTI. As a reference for the different types of data produced by the ILS and MBTI instruments, see the tables 1 and 2 below.

Table 1. ILS Learning Style Categories
**Literature Review**

Research in engineering education over the past few decades shows a general call for reform in pedagogy. Though considerable strides have been made in terms of adapting traditional teaching methods to meet the needs of new student generations, understandable voids still exist. Throughout this section, we discuss where the research has been focused in improving engineering education by better understanding ways that people learn. This review involves studying and analyzing active learning tools and techniques, along with the assessment methods for determining their efficacy.

When Felder investigated learning and teaching styles in engineering education during the late 1980s, there was quite a response from the community [10]. Felder sought to explain common pitfalls in engineering classrooms and propose a plan to improve engineering education as a whole. Drawing on the research of Kolb, Myers, and Piaget [11], Felder looked to implement educational psychology research for his own practical purposes and for direct use in the classroom. He recognized divergences between the way most engineering students tend to learn and the way most instructors tend to teach. As early as the 1990s, engineering educators found themselves deep in the throws of this new transition of understanding the old, traditional approach for teaching engineering curriculum versus new, innovative possibilities. The traditional passive role of students is to be listeners during lectures. Any “doing” comes after
class in the form of labs or homework. Felder later discusses these Changing Times and Paradigms [12], considering active learning as the new frontier, pushing for “stimulating interactive lessons.” Smith and Waller build upon the educational reforms and lay out New Paradigms for Engineering Education [13], which include conducting assessments in various forms to summarize the impact of active learning methods.

When it comes to active learning, the art of teaching with student engagement in mind is at the heart of the matter. Smith pinpoints the creativity involved in thinking about “How do you learn best?” and challenges educators to have more fun with both curriculum and instruction [14]. With a focus on a particular active learning strategy, called cooperative learning, a consideration of how FE based ALMs fit into the interactions present in the classroom is warranted. Prince reviews the active learning research and provides evidence indicating that active learning improves understanding [15]. No matter the magnitude of improvement levels, it is important to note that the overwhelming response to active learning studies is positive. In an international effort, Bernhard reports on the need for long-term results to be reviewed [16]. When computer science students were studied [17], increased comprehension and skills due to implementation of active learning techniques were reported. These students were thought to be the furthest from needing any form of active pedagogy, as they are often generalized as individualistic, introverted and non-social learners. Vallino goes on to discuss the need for active learning techniques, especially problem-based learning, in software development curriculum [18]. Through this approach, students reported better test scores and appreciation for the course.

There are several efforts [19, 20] implementing hands-on engineering initiatives that lead to the discovery of “excitement of learning by doing!” The state-of-the-art in active learning involves personalized learning [21] where lessons are automatically adapted to fit students individual learning needs and style. “SMART” learning has been employed to develop intelligent distributed environments for active learning [22]. The common thread throughout all these efforts is the focus on student-centered learning to improve education efforts.

Wood and Jensen have collaborated on several hands-on curriculum designs as well as the development and deployment of Active Learning Products (ALPs) to take the field of active learning in exciting new directions. Hands-on activities provide students of all learning styles and personality preferences the opportunity to get actively involved with their learning and
provides for valuable experience useful in future industry work [23-25]. The idea of incorporating MBTI data has been previously examined by [26, 27]. Our latest work includes the development of assessment techniques to explore the equitability of effectiveness of the active learning techniques across different student demographics [7, 8]. From this work, we created an innovative assessment algorithm that can be adapted to assess a wide variety of active learning products. Additionally, this work highlights preliminary results of ALMs, in the form of tutorials, enhancing student learning of difficult course content.

In recent years, Felder participated in several research studies [28-30] to validate both learning styles and MBTI effects to understand student differences to a further degree. Validation aside, there exists camps of educational researchers that resist the idea of learning styles [31-33]. Resistance and disagreement exists for several reasons, such as the lack of psychological studies that validate the actual existence of learning styles. In addition, the cognitive science community is conflicted on the validity of these techniques. Even with varying opinions, there have been numerous efforts to use the concept of learning style to further understand how students differ, how educators can reach all students, and how to enhance learning [34-36].

This research is breaking into a new sector of combining active learning with assessment measurements for equitability correlations using the Felder-Soloman learning styles and MBTI indicators. The overarching theme is the combination and extension of several useful tools to develop innovative ALMs combined with a hybrid assessment method. Disagreement with the learning styles is accepted but arguably inconsequential for this work, and does not discredit the novelty of these ALMs and the assessment method in general. Currently, there are three “Assessment of Student Achievement” projects being funded by NSF’s Course Curriculum and Laboratory Improvement (CCLI) programs; all varied in topics. One aims at developing a “Computerized Adaptive Dynamic Assessment of Problem-solving,” another endeavors to validate engagement measurements. Our current study remains unique from what is being researched and executed in the classroom to date. It is clear that the global engineering community is discovering the potential of experiential learning environments and the corresponding need for effective assessment methods to determine intended quality and improvement of the learning process [37].
Finite Element Based ALMs

As an example of a ALM, consider the “Curved Beam” tutorial. One of the first decisions when creating an ALM is the choice of finite element software. Our ALMs use a number of different commercial software packages. For the “Curved Beam” ALM, the SolidWorks software was chosen. Besides meeting most of the considerations mentioned above, this software was attractive because participating students had introductory SolidWorks experience in freshman graphics courses. For the curved beam problem, the foundations were drawn from the literature, such as fundamentals from the well-known text *Mechanical Engineering Design* (Shigley, 8th edition). After initial testing, the problem could be solved by students using the module in an average of 40 minutes. With most students spending 60 to 90 minutes on homework problems, this average met desired goals of the module developers.

This specific topic was chosen for development of an ALM because students have a difficult time visualizing stress distributions in curved beams and calculating the radius of the neutral axis. Therefore, problem analysis objectives for the ALM include assisting students in determining the stress distribution, using the FE method to visually verify this distribution and using the FE method to visually verify the location of the radius of neutral axis. Educational objectives for the module itself include providing students with a basic understanding of the FE method, associated constraints and boundary conditions, methods of model verification and experience with commercial FE software. Once software has been chosen and the specific topic of study has been identified, the step-by-step procedure for the ALM is developed. Ideally, each module will take students through a step-by-step process similar to the following:

⇒ Verify SolidWorks is loaded on computer
  o Open existing model in SolidWorks Simulation
  o SolidWorks Simulation study folders
⇒ Overview of SolidWorks
  o Left side of SolidWorks window
  o Use of SolidWorks interface
  o Toolbar explanation
  o Tutorials and getting help
⇒ Creating SolidWorks model
  o Setting the drawing units to inches
  o Assigning material properties to model
  o Applying constraints and boundary conditions to model
  o Creating split-line force to model
⇒ Meshing the model and running the study
Building on this example, each ALM was developed with a common template presented as follows:

- Module title, author, contact information, expected completion time and references
- Table of contents
- Project educational objectives based upon ABET Criteria 3 for Engineering
- Problem description and analysis objectives
- General steps and specific step-by-step analysis
- Viewing the results of the FE analysis and comparison to another technique
- Summary and discussion
- Background information on FE theory

Figure 1 shows the template “Module Title Page” implementation for the “Curved Beam” module.

Figure 1. Curved Beam Module Title Page
Assessment Approach

In order to achieve the project assessment goals, an assessment methodology is fully developed as outlined in Figure 2. To start, the ALM, the FE module in this case, is created. Before distributing the module, however, an evaluation content quiz [38] (example in Fig. 3) is created and demographic data are gathered from the students. Once the pre-quiz is administered, the module may be implemented. The post-quiz, identical in content to the pre-quiz, is taken after completion of the module. The students complete an in-depth survey (example in Fig. 4) when finished. The survey allows the student to be an active member in this iterative improvement cycle. Once all the demographic data and quiz scores have been linked with common student identification, the assessment process may move to the statistical analysis phase.

Figure 2. Equitability Correlations Assessment Method (ECAM) Deployment

Figure 2 summarizes the assessment approach. This assessment algorithm provides two opportunities for iterative feedback with the student: surveys and confidence intervals. Students have a direct opportunity to express their opinions about how well the modules enhanced their learning experience. The equitability correlations are carried out using confidence intervals and are explained in detail in the precursor to this work [7, 8].
The content quiz used for the “Curved Beam” Tutorial is as follows:

Circle the best answer

1. The normal stresses at points at A0, A1, A2, and A3 are the same.
   a) True  b) False

2. The normal stresses at points at A0 and D0 have the relation as follows.
   a) \( \sigma_{A0} > \sigma_{D0} \)  b) \( \sigma_{A0} < \sigma_{D0} \)  c) \( \sigma_{A0} = \sigma_{D0} \)

3. The stress at the center of the cross section area is zero.
   a) True  b) False

4. The maximum normal stress occurs at the following sections:
   a) A0-A3 section  b) D0-D3 section  c) Both A0-A3 and D0 –D3 sections.

5. The shear stress at any points located on the cross-section A0-A3-D0-D3 is zero.
   a) True  b) False

6. The maximum stresses on section A0-A3 is equal to its normal stress.
   a) True  b) False  c) The question doesn’t make any sense.

7. The maximum shear stress occurs on section A0-A3.
   a) True  c) False  c) Both answer are wrong.

8. The stress distributions on Section H – H and Section I – I are the same.
   a) True  b) False

9. The stress level of the hook’s left portion from section J – J is zero.
   a) True  b) False

Figure 3. Beam bending basic knowledge quiz (pre and post for Curved Beam Tutorial).
The following is an example of a survey used, as discussed, for student feedback:

Please put an X in the box below that corresponds to your answer.

<table>
<thead>
<tr>
<th>Question</th>
<th>Disagree</th>
<th>Partly Disagree</th>
<th>Neither Agree nor Disagree</th>
<th>Partly Agree</th>
<th>Agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>This activity helped me understand “curved-beam bending” in a conceptual manner.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>This activity helped me to understand the stress distribution in the curved beam.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>This activity helped me to visualize the stress distribution in the curved beam.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>This activity helped me to have a better understanding about the deformation of the curved beam under the concentrated load.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>This activity will help me to design a better curved beam to undertake a larger load.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>This activity helped to locate the points where the normal stress is zero.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Activities like this one doesn’t require full understanding of the finite element theory.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>This activity helped me to create a correct FE model from 3D CAD model for stress analysis.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>This activity helped me to learn how to apply the force, add constrains and create meshes for FE model.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>After completing this activity, I was able to implement a simple FE analysis using COSMOS.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>This activity was more effective than class time for lecture or board-work in terms of understanding the stress distribution.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The FE analysis method is more useful and efficient to get all stress information for a structural member.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I would like to learn more on using the finite element method to solve other mechanical engineering design problems.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Totals                                                                 |          |                 |                            |              |       |
| Percentage of Students Selecting Response                               |          |                 |                            |              |       |

Figure 4. Sample students survey

The next significant step in the assessment process is the calculation of statistical correlations. Once an evaluator decides upon a demographic group to study, the student quiz score results are grouped according to the chosen demographic. Common empirical numbers may be analyzed, e.g., mean, mode, median. Specifically, the analysis is used to determine if the performance differences, *deltas* ([post-quiz score] minus [pre-quiz score]), are statistically
distinct between pairs of learning styles and personality types. In order to determine this distinction, the data are treated as a sample of a theoretical larger population. Student-t distributions are used for the statistical analysis, as the sample sizes are relatively small for this study. Using confidence intervals, the evaluator determines if there is any significant statistical difference between how the FE module is reaching individual students across demographic groups. For example, if an extroverted group has an average delta smaller than the introverts, confidence intervals measure the likelihood of a practical difference existing.

The data collected for this work is a part of the NSF funded CCLI project analogous with the FE ALM development. Several universities across institution type and student diversity assisted in implementing each module in corresponding engineering classrooms. Professors were given previously developed modules along with other tools and then asked to return as much data as possible. The tools and data used in this work are discussed below.

The breadth of resources used throughout this assessment process covers a significant breadth of research standards. Professors traverse the process of using the tools provided to produce learning and assessment data. Resources classified as tools include each of the FE modules, the corresponding content quiz used for pre- and post-evaluation, student surveys, and the learning style and personality type index resources. The Felder-Silverman index of learning styles and the MBTI were chosen as assessment qualifiers. Though MBTI varies slightly from strict personality types, we will differentiate between the two demographics simply as learning styles and personality types. Informal tools that arose during the study include professor feedback and quiz validation. Data sets studied include results of pre- and post-quizzes, indices inventories and survey responses. Specifically, the assessment work focuses on the results that correlate the quiz scores to learning styles and personality type. More generally, the global improvements in quiz scores can help determine the effectiveness of the modules as active learning tools.

**Results**

Below, we show results for two specific demographic correlations using a representative ALM; in this case the Heat Transfer Finite Element Module. As shown in Table 3, the students in this particular class used the ILS questionnaire to determine their learning styles ([http://www.engr.ncsu.edu/learningstyles/ilsweb.html](http://www.engr.ncsu.edu/learningstyles/ilsweb.html)). The pre- and post-quiz results were
categorized based on the learning styles of the students. Small sample statistics (student t-test) were used to provide the statistical analysis. The students took the pre-quiz, then completed the ALM and then took the post-quiz. The percentage improvements between the pre- and post-quiz are recorded in Table 3 for each of the learning style categories. Recall that the learning style categories are paired. So a student is either “Active” or “Reflective”, either “Sensing” or “Intuitive”, either “Visual” or “Verbal” and either “Global” or “Sequential.” Therefore the average delta computed as

\[\text{Delta} = \left(\frac{\text{postquiz} - \text{prequiz}}{\text{prequiz}}\right) \times 100\]

is found and compared for each of these pairs of learning styles. The goal of this analysis is to determine if one learning style is benefiting more from the ALM than another learning style. From Table 3, note, for instance, that the Delta (improvement) for the “Reflective” learners is 14.3% while it is only 6.3% for the “Active” learners.

Table 3. Heat Transfer Results (Learning Style Pairs)

<table>
<thead>
<tr>
<th>Learning Style</th>
<th>Active</th>
<th>Reflective</th>
<th>Sensing</th>
<th>Intuitive</th>
<th>Visual</th>
<th>Verbal</th>
<th>Global</th>
<th>Sequential</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Students</td>
<td>9</td>
<td>3</td>
<td>5</td>
<td>7</td>
<td>10</td>
<td>2</td>
<td>5</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>Delta (improvement)</td>
<td>6.3</td>
<td>14.3</td>
<td>5.7</td>
<td>10.2</td>
<td>8.6</td>
<td>7.1</td>
<td>11.4</td>
<td>6.1</td>
<td>8.7</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>17.7</td>
<td>14.3</td>
<td>16.3</td>
<td>17.9</td>
<td>18.1</td>
<td>10.1</td>
<td>21.2</td>
<td>13.9</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 4 shows confidence intervals for the pairs of data in Table 3. The confidence intervals answer the question: are the averages in Table 3 really statistically different? The number of data points, averages and standard deviation are used in standard small sample size (student-t) manner to compute these confidence intervals. Note that, despite the small sample size, most of the data (those with greater than or equal to 5 points) falls within the accepted sample sizes for the “student-t” statistical analysis methods. Note in Table 4 that the largest
value is associated with the differences in the averages for “Reflective vs. Active” data. Specifically, there is a 52.3% chance that the 6.3 and 14.3 average values for “Active” and “Reflective” learners in Table 3 are actually different. Restated in the nomenclature of this present research, there is a 52.3% chance that the “Reflective” learners benefit more from the ALM than do the “Active” learners.

Table 4. Heat Transfer LS Correlations

<table>
<thead>
<tr>
<th>Learning Style Differences</th>
<th>Confidence Interval (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reflective vs. Active</td>
<td>52.3</td>
</tr>
<tr>
<td>Intuitive vs. Sensing</td>
<td>33.8</td>
</tr>
<tr>
<td>Verbal vs. Visual</td>
<td>10.9</td>
</tr>
<tr>
<td>Sequential vs. Global</td>
<td>35.8</td>
</tr>
</tbody>
</table>

The MBTI based data shown in Tables 5 and 6 follows the same analysis pattern as that for the learning styles data in the previous two tables. Note in Table 5 that there are large differences in the standard (unweighted) deltas for the “iNtuitors vs. Sensors”, Thinkers vs. Feelers” and for the “Judgers vs. Perceivers.” The weighted delta data shows large differences between the “Thinkers vs. Feelers” and also for the “Judgers vs. Perceivers”. These large deltas lead to large confidence intervals as shown in Table 6.

Table 5. Heat Transfer Results (MBTI Pairs)

<table>
<thead>
<tr>
<th>Personality Types</th>
<th>Extrovert : Introvert</th>
<th>iNtuitor : Sensor</th>
<th>Thinker : Feeler</th>
<th>Judger : Perceiver</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Students</td>
<td>5 : 7</td>
<td>8 : 4</td>
<td>6 : 6</td>
<td>10 : 2</td>
<td>6</td>
</tr>
<tr>
<td>Delta (improvement)</td>
<td>8.6 : 8.2</td>
<td>10.7 : 3.6</td>
<td>4.8 : 11.9</td>
<td>36.8</td>
<td>8.4</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>21.7 : 13.9</td>
<td>16.6 : 18.0</td>
<td>17.3 : 16.7</td>
<td>18.1 : 0.0</td>
<td>-</td>
</tr>
</tbody>
</table>

Specifically note the values in Table 6 which are over 50%. These values indicate that there is greater than a 50% chance that one MBTI type is receiving greater benefit from the ALM than the opposite MBTI type. These circumstances indicate opportunities for iterative, directed
refinement of the ALMs. In this particular case, since the MBTI-Thinker and the MBTI-Judger groups did not benefit as much as their counterparts (MBTI-Feeler and the MBTI-Perceiver groups respectively), the iterative refinement plan calls for specific steps that should enhance the active learning experience for these two groups. For example, to improve the experience for the MBTI-Thinkers, reformatting the homework questions after the module in a way that leads the student through a step-by-step, logical process to increase their understanding of the physical principles being modeled should fit well with the “thinkers” preferences. In addition, making sure that the instructions in the FE modules include explanations indicating what specifically a step in the simulation process is accomplishing should also enhance the experience for the MBTI-Thinkers. To enhance the ALM for the MBTI-Judgers, one critical item is to have an accurate estimate of the time needed to complete the ALM. Also, a detailed outline of the ALM content and process will allow the MBTI-Judgers to schedule their work and keep track of their progress.

Table 6. Heat Transfer MBTI Correlations

<table>
<thead>
<tr>
<th>MBTI Differences</th>
<th>Confidence Interval (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Introvert vs. Extrovert</td>
<td>2.8</td>
</tr>
<tr>
<td>Sensor vs. INtutor</td>
<td>46.4</td>
</tr>
<tr>
<td>Feeler vs. Thinker</td>
<td>51.4</td>
</tr>
<tr>
<td>Perceiver vs. Judger</td>
<td>60.6</td>
</tr>
</tbody>
</table>

While Tables 3-6 show an example of the learning styles and MBTI correlation studies, Table 7 shows the overall results cumulatively for all 12 ALMs. These sets of data can be addressed very methodically. First, there are a total of 12 ALMs to assess, each with unique subject matter from structural engineering to electrical engineering. Then, the number of who students participated in the module pilot study can be determined. Almost 150 students participated in the first round of each FE learning module implementation into the classroom setting. An average of 12 students were in each class using the ALM to supplement the curriculum. For each ALM, the average pre-quiz score for the groups of students can be seen, ranging from 42% to 71% correct. The overall average of all pre-quiz scores pertaining to all 12
FE modules was 58.6%, well below passing. The overall post-quiz average of 75.5% jumps just over passing, with an individual range on the 12 modules of 65% to 82% correct. Results indicate that on average, students are not passing the content pre-quiz, but after being administered the module, the average student improves their post-quiz score to above passing. On a strictly percentage base improvement scale, it becomes clear that there is an average delta of almost 17 raw percentage points. This can be directly translated as grade enhancement of a letter grade and a half. Looking at the improvement on a relative percentage bases, there is an average improvement of 30%. For example, on the Microstrip Antenna Design module, scores improve from an average of 60% to over 80%, rounding out to an improvement of 35.5%. The range of percentage improvements starts at about 15% and goes up to nearly 60% improvement.

Table 7. Cumulative Global Results of FE Modules based on Student Performance

<table>
<thead>
<tr>
<th>FE Learning Module Subject</th>
<th>Students</th>
<th>Pre-Quiz Avg</th>
<th>Post-Quiz Avg</th>
<th>Delta</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Curved Beam Structural Analysis</td>
<td>9</td>
<td>71.1</td>
<td>82.2</td>
<td>11.1</td>
<td>15.6%</td>
</tr>
<tr>
<td>Stiffness Bolt Structural Analysis</td>
<td>12</td>
<td>55.8</td>
<td>65.0</td>
<td>9.2</td>
<td>16.4%</td>
</tr>
<tr>
<td>Long Bar Heat Transfer</td>
<td>19</td>
<td>63.1</td>
<td>72.9</td>
<td>9.8</td>
<td>15.5%</td>
</tr>
<tr>
<td>L-Bracket Transient Heat Transfer</td>
<td>19</td>
<td>63.1</td>
<td>72.9</td>
<td>9.8</td>
<td>15.5%</td>
</tr>
<tr>
<td>Biomedical Electromagnetics</td>
<td>6</td>
<td>50.0</td>
<td>76.7</td>
<td>26.7</td>
<td>53.3%</td>
</tr>
<tr>
<td>Fluid Dynamics Cylinder Drag</td>
<td>7</td>
<td>62.9</td>
<td>77.1</td>
<td>14.3</td>
<td>22.7%</td>
</tr>
<tr>
<td>Fluid Dynamics Friction Flow</td>
<td>7</td>
<td>62.9</td>
<td>77.1</td>
<td>14.3</td>
<td>22.7%</td>
</tr>
<tr>
<td>Vibration of Cantilever Beam</td>
<td>7</td>
<td>49.9</td>
<td>79.6</td>
<td>29.7</td>
<td>59.6%</td>
</tr>
<tr>
<td>Vibration of Tapered Beam</td>
<td>16</td>
<td>58.0</td>
<td>72.3</td>
<td>14.3</td>
<td>24.6%</td>
</tr>
<tr>
<td>Microstrip Antenna Design</td>
<td>10</td>
<td>60.0</td>
<td>81.3</td>
<td>21.3</td>
<td>35.5%</td>
</tr>
<tr>
<td>Sar Analysis</td>
<td>20</td>
<td>63.8</td>
<td>81.5</td>
<td>17.7</td>
<td>27.7%</td>
</tr>
<tr>
<td>2D Transmission Lines</td>
<td>10</td>
<td>42.5</td>
<td>67.5</td>
<td>25.0</td>
<td>58.8%</td>
</tr>
<tr>
<td><strong>Total:</strong></td>
<td><strong>142</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>AVERAGES:</strong></td>
<td><strong>11.83</strong></td>
<td><strong>58.6</strong></td>
<td><strong>75.5</strong></td>
<td><strong>16.9</strong></td>
<td><strong>30.7%</strong></td>
</tr>
</tbody>
</table>

These cumulative results allow us to take a global perspective on the effectiveness of the modules. As active learning products, we asked if these particular ALMs were enhancing student learning. From these initial results the following conclusions can be drawn:

1. On average, the ALMs assist students learning the material with about a 30% improvement to content knowledge,
2. Student quiz scores improve from below passing to above passing by almost two letter grades on average, and
3. The modules have been piloted in 12 different classrooms. With even one iteration of refinement, the potential opportunity for improved learning appears to be significant.
Conclusion and Future Work

Active learning provides future engineers with the opportunity to be more involved in their own education. To date, 12 Finite Element (FE) based Active Learning Modules (ALMs) have been designed and developed using active learning pedagogical foundations. The specific topics for the ALMs were chosen from topics that historically have been difficult for students to comprehend and which could be modeled using FE analysis. The two project goals were to use active learning to enhance student understanding of these difficult engineering concepts using FE based ALMs and to increase exposure and understanding of the FE method for undergraduate engineers. In order to accomplish these goals, an extensive assessment strategy was developed. The strategy, and associate assessment instruments and processes, are designed to accomplish two assessment goals: 1) to determine if the ALMs enhance the learning process for the students and 2) to determine if the ALMs benefit one student demographic group more than another group. The assessment/student demographic correlations allow us to iteratively enhance the ALMs to make them more effective across all student demographic groups.

The cumulative results of all 12 FE based ALMs were very positive. From the correlations, areas of improvement for future iterations of particular ALMs are identified. On a whole, the average improvement to student learning directly related to these ALMs is significant. The ALMs are providing students with the chance to go from below passing on content quizzes to above passing. Specifically, the assessment over the 12 ALMs indicates an average pre to post quiz increased score of over 30%. The iterative assessment method (based on the equitability correlations) has identified numerous demographic groups that benefited less than other groups from the implementation of the ALMs. This provides the potential to refine and improve each ALM in order to proceed toward the goal of equitable benefit from the ALMs across numerous student demographic groups. It also provides the motivation, background, resources, and evaluation tools as a model way to incorporate and assess pedagogy and curriculum development that improves engineering education.
Acknowledgments

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