

# **AC 2009-2076: A NOVEL ASSESSMENT METHODOLOGY FOR ACTIVE LEARNING MODULES TO EQUITABLY ENHANCE ENGINEERING EDUCATION**

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# **A Novel Assessment Methodology for Active Learning Modules to Equitably Enhance Engineering Education**

## **Abstract**

Active learning consists of pedagogical approaches to address the broad spectrum of students in engineering programs and their varied educational backgrounds and demographics. In this paper, the focus is on a particular type of active learning module, known as tutorials. We have developed and assessed 12 Finite Element based learning modules covering a number of fundamental topics in Mechanical, Electrical, and Biomedical Engineering. As part of this research, we have developed more fundamental and informative assessment strategies for active learning approaches. The intent of this extended assessment process is to discover potential inequities across a range of demographic and student-learning variables. In particular, the results of the pre- and post-quizzes are correlated with demographic and student-learning variables. Statistical analysis is used to determine if certain student groups benefit more from the learning modules than other groups. Results of this process show that, overall, the finite element tutorials lead to enhanced student learning (compared to a “control” group) and can span across student demographics without undo preference for certain student learning styles or personality types. However, certain cases do exist where unique learning styles or personality types respond more positively to this pedagogical technique than others. The opportunity for iterative feedback will lead to subsequent improvements. The most important, and contributory, result is an exciting new algorithm to perform this type of assessment across active learning approaches.

## **Introduction**

As educators move forward in advancing engineering education, active learning tools are a viable choice for addressing how students struggle with complex topics in engineering, especially as a function of their backgrounds, demographics, and personality types. In order to get beyond the typical road bumps encountered when teaching difficult application methods, contemporary methods are being developed that seek to engage students actively, both inside and outside the classroom, as well as kinesthetically through the varied human senses. Such approaches have the potential to improve student comprehension and knowledge retention, and, most importantly, to increase students’ interest in the material<sup>51</sup>.

Assisting students in the learning of imperative analysis tools is especially important with the current techniques used in industry. One such technique is finite element analysis. The finite element (FE) method is widely used to analyze engineering problems in commercial engineering firms. It is an essential and powerful analytical tool in designing products with ever-shorter development cycles<sup>6-8</sup>. In the past, consulting firms needed Ph.D. and M.S. engineering graduates to analyze designs with FE, but recently these firms<sup>6,8</sup> are asking their B.S. and A.A.S. engineering graduates to learn and apply this complex analysis technique. In many undergraduate programs, the FE method is not taught as a required element thus graduates often lack knowledge of the proper use of this tool<sup>26,27</sup>. Two principle reasons for this are:

1. Introducing new material in curriculum typically requires the removal of other material (possibly essential by the faculty and ABET.) This approach must be balanced with the recent push to reduce total credit hours of programs nationwide.

2. FE coursework typically is organized around theoretical details considered more appropriate for graduate students who may have a more rigorous mathematical education than undergraduate students.

The basic FE method is currently offered as an elective introductory/senior project course in mechanical, civil, and aeronautical engineering programs<sup>1,2,5,9,11</sup>. However, more effective instructional methods may be available to a broader spectrum of students if FE analysis is sequentially integrated throughout required engineering courses<sup>3,4,10</sup>

An important goal of this work is to educate diverse undergraduate engineering students with a basic knowledge of FE theory, along with practical experience in applying commercial FE software to engineering problems. The lack of experience in using numerical computational methods in designing structural solutions is a noted problem for some engineering graduates<sup>26,27</sup>. Accreditation Board for Engineering and Technology, Inc. (ABET, Inc.) expects engineering graduates to have: “an ability to use the techniques, skills, and modern engineering tools necessary for engineering practice”<sup>14</sup> such as FE analysis. Hence, schools have, or are planning to, add FE analysis to their curriculum<sup>1-5,10</sup>, but this plan is not happening quickly enough to meet the demand of firms competing in the global economy. To support schools in their teaching efforts, the finite element exercises developed in this work will provide a valuable, web-based resource to engineering instructors throughout the world.

An NSF funded Course, Curriculum, and Lab Improvement (CCLI) proof-of-concept project that corresponds with this work aims at developing FE tutorials. These learning modules can be easily implemented in “traditional” undergraduate engineering courses. The FE learning modules provide students with hands-on experience in FE method applications in problem modeling. The models include problem definition, project educational objectives, analysis approach, assumptions, goals, and comparison to hand calculations or experimental data, following a unique learning cycle known as Kolb’s cycle. To scaffold learning for those unfamiliar with the commercial FE software, students are provided with systematic, step-by-step procedures of modeling.

Initially, we have developed FE learning modules in six engineering areas: (1) structural analysis, (2) mechanical vibrations, (3) fluid mechanics, (4) heat transfer, (5) electromagnetics, and (6) biometrics. To evaluate these modules, they are integrated into existing courses in the corresponding subject areas. Faculty and students initially assess the effectiveness of the modules at three higher educational institutions. The project team is composed of experienced and well-qualified engineering educators at these institutions along with an engineering educator and independent evaluators at three other higher education institutions.

The independent evaluators develop the *project assessment goals*. To analyze the effectiveness of the FE tutorials, a level of improved understanding is calculated by relating quiz scores to learning styles and personality types, followed by the application of basic statistical analysis. The end goal is to accurately and comprehensively assess the quality of the learning modules and whether they are equally serving students across different demographics and other factors. These assessment goals will be accomplished through three *project assessment objectives*:

1. *Assessment Methodology*. Develop and implement an iterative assessment system.

2. *Statistical Measures.* Determine improvement in student learning across distributions.
3. *Equitability Study.* Gain insight into the effectiveness of the FE learning modules across various personality types and learning styles.

As a basis for our study, this paper presents the results of four FE tutorials, gathering raw data from each student group, and assessing the spread of educational gain across demographics, personality types, and learning styles of the groups. In the end, the developmental path of a generalized assessment methodology, which we coin as the “Equitability Correlations Assessment Method (ECAM),” is paved. The following section discusses the pedagogical foundations of the project, including the aforementioned Kolb Learning Cycle.

## Background and Literature Review

### *Kolb Learning Cycle*

The pedagogical foundations for this project are based upon the *Kolb Learning Cycle*<sup>23-25, 33</sup>. The Kolb model [Fig. 1] describes a cycle around which learning experiences progress. The Kolb Learning Cycle improves student retention of the complex numerical procedure involved in FE analysis. During courses integrating FE learning modules, students are introduced to FE theory within their traditional lectures. Professors cover background of the FE method, fundamental mathematics of FE, the topology of the various finite elements, error analysis of FE results, and how to model engineering problems using this technique. Portions of Kolb’s cycle are interlaced with hands-on activities that begin stating the proposed problem in a real-world manner. FE learning modules provide specific instructions on how to build the FE model of the engineering problem to increase student performance in the analysis for “*Concrete Experience*” on Kolb’s cycle.

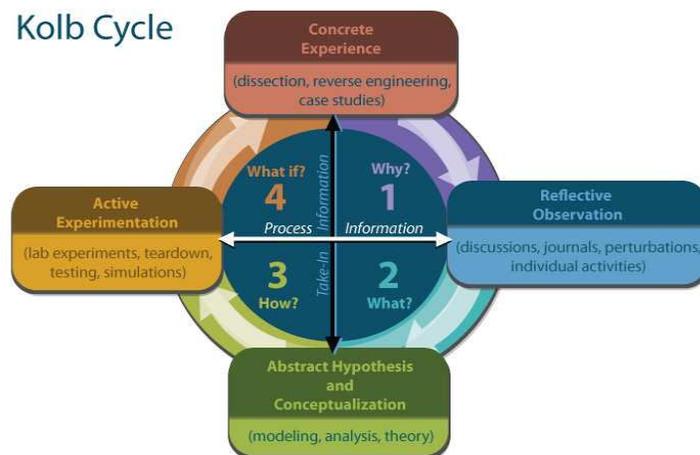


Figure 1. Kolb learning cycle.

### *Learning Styles*

Each FE learning module developed in this work is designed to span a spectrum of different characteristics in which students learn. Felder-Soloman Index of Learning Styles<sup>50</sup> is composed of four dimensions: active/reflective, sensing/intuitive, visual/verbal, and sequential/global [Table 1]. Active learning tools are designed to meet the needs of students with a range of learning styles. Particular approaches to teaching often favor a certain learning preference.

Therefore it is important to incorporate a variety of teaching approaches This index can assist instructors in creating active learning modules that impact all student learning styles effectively.

Table 1. Learning Styles categories.

Felder-Soloman	
<b>ACTIVE</b> Doing something active with it. Discussing, applying, or explaining it to others.	<b>REFLECTIVE</b> Thinking about it quietly first.
<b>SENSING</b> Learning facts.	<b>INTUITIVE</b> Discovering possibilities and relationships.
<b>VISUAL</b> See-- pictures, diagrams, flow charts, time lines, films, and demonstrations.	<b>VERBAL</b> Words-- written and spoken explanations.
<b>SEQUENTIAL</b> Gain understanding in linear steps.	<b>GLOBAL</b> Learn in large jumps, suddenly "getting it."

Table 2. Overview of the MBTI categories<sup>43</sup>.

Overview of MBTI	
<b>Manner in Which a Person Interacts With Others</b>	
<b>E</b> Focuses outwardly. Gains energy from others.	Focuses inwardly. Gains energy from cognition. <b>I</b>
<b>EXTROVERSION</b>	<b>INTROVERSION</b>
<b>Manner in Which a Person Processes Information</b>	
<b>S</b> Focus is on the five senses and experience.	Focus is on possibilities, use, big picture. <b>N</b>
<b>SENSING</b>	<b>INTUITION</b>
<b>Manner in Which a Person Evaluates Information</b>	
<b>T</b> Focuses on objective facts and cause & effect.	Focuses on subjective meaning and values. <b>F</b>
<b>THINKING</b>	<b>FEELING</b>
<b>Manner in Which a Person Comes to Conclusions</b>	
<b>J</b> Focus is on timely, planned decisions.	Focus on process oriented decision-making. <b>P</b>
<b>JUDGEMENT</b>	<b>PERCEPTION</b>

**Myers Briggs Type Indicator (MBTI) Personality Type**

The Myers Briggs Type Indicator (MBTI) is similar to Felder-Silverman Learning Style, but is linked to personality preferences [Table 2]. MBTI includes four categories of how an individual processes and evaluates information<sup>43</sup>. The first category describes how a person interacts with his or her environment. People who take initiative and gain energy from interactions are known as *Extroverts (E)*. *Introverts (I)*, on the other hand prefer more of a relatively passive role and gain energy internally. The second category describes how a person processes information. People who process data with their senses are referred to as *Sensors (S)*, and a person who sees where data is going in the future is called an *iNtuitior (N)*. The *Sensor* versus *iNtuitior* category is an interesting area of study when it comes to engineering education, because professors are historically intuitors while most engineering students are sensors<sup>50</sup>. The third category for MBTI preference describes the manner in which a person evaluates information. Those who tend to use

a logical cause and effect strategy, *Thinkers (T)*, differ from those who use a hierarchy based on values or the manner in which an idea is communicated, *Feelers (F)*. The final category indicates how a person makes decisions or comes to conclusions. *Perceivers (P)* prefer to be sure all the data is thoroughly considered, and *Judgers (J)* summarize the situation as it presently stands and make decisions more quickly.

A number of researchers have used knowledge of MBTI types to enhance engineering education<sup>23,33,44,45</sup>. In this prior educational research, it has been shown that different MBTI types respond in unique ways to distinctive pedagogical approaches. The goal of using the MBTI data in concurrence with learning modules is to ensure the FE tutorials are effective across different personality types, bringing any of these nuances to light. The innovative step to our analysis here is to take the assessment one step beyond effectiveness. We are looking into how equally this effectiveness reaches across demographic groups, learning styles, and personality.

## **Assessment Methodology**

### ***FE Learning Modules***

A starting point for our educational objectives is the development of the FE tutorials. Each learning module is pedagogically rooted in active learning based on Kolb's learning cycle. By completing the cycle fully, the student will have a stronger grasp on the difficult engineering and FE material. As an accompaniment to traditional lectures, the tutorials help guide students through active experimentation, concrete experiences, and reflective observation.

The FE learning modules are designed for those students who have little to no experience using the FE analysis. Therefore, the basic nature of the problems makes it more possible that the students will grasp the correlations between the physical solution and the computational model. Each tutorial was developed in PowerPoint and is available in ppt and pdf file format. Each FE tutorial was developed with a common template presented as follows:

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

The FE learning modules have been initially linked to one of four commercial FE codes (COSMOSWorks, ANSOFT, MSC.Nastran, or COSMOSFloWorks) all commonly used in industry. The following four FE learning module topics are the focus of this paper:

1. Steady-state Heat Transfer in a Bar
2. Bolt and Plate Stiffness
3. Curved Beam

#### 4. Lateral Vibration of Tapered Cantilever Beam

These four modules, as part of the entire set of 12 Finite Element learning modules, are a refreshing first step to filling a current void in engineering education. Their benefits, along with the assessment methodology developed in this paper, have the potential to be far reaching.

##### ***Assessment Foundations***

Helpful steps to assessments for the FE tutorials are: (a) gathering student demographics (i.e. academic major, educational level, grade point average, expected grade earned in current course, reason for taking course, plans after graduation, age, ethnicity, and gender); (b) gathering Felder-Silverman learning style and MBTI personality type (this analysis, along with learning objectives, can be reviewed and fed back into improving the learning modules); and (c) collecting all data and linking these data to a common student identification number for future evaluations and survey responses.

The next step is developing an assessment instrument for evaluating student learning. In this work, a multiple-choice quiz is used as the foundation. The quiz is administered after the FE material is presented in class, but prior to the student being introduced to an FE learning module. Ideally, isolating complementary tutorial based enhancement in understanding of the difficult FE theories and methods, and associated engineering topic content. The same quiz is administered following the completion of the tutorial. The pre-quiz and post-quiz scores are again linked to the common student ID. In parallel, as soon as the student completes the FE learning module, an in-depth survey is administered to the students, providing the opportunity for much more open feedback to the assessment system.

##### ***Assessment Algorithm***

To achieve the project assessment goals an assessment methodology is fully developed [Figure 2]. To start, the learning module, the tutorial in this case, is created. Before distributing the tutorial, however, an evaluation quiz is created and the demographic data gathered from the students. Once the pre-quiz is completed, the tutorial is implemented and the post-test is subsequently administered. The students complete an in-depth survey after the tutorial is 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 statistical analysis.

The next large step in the assessment process is the statistical correlations. Once an evaluator decides upon a demographic group to study, the student quiz score results are grouped accordingly. Common empirical numbers may be analyzed, e.g., mean, mode, median. Specifically, we are interested in determining if the “Deltas” [(post-quiz score) minus (pre-quiz score)] are statistically distinct between the pairs of learning styles and personality types. In order to determine this, 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 educational evaluator determines if there is any real statistical difference between how the FE tutorial is reaching individual students across demographic groups. For example, if an extroverted group has an average delta smaller than the introverts, a confidence interval is a measure for the likelihood that differences exist

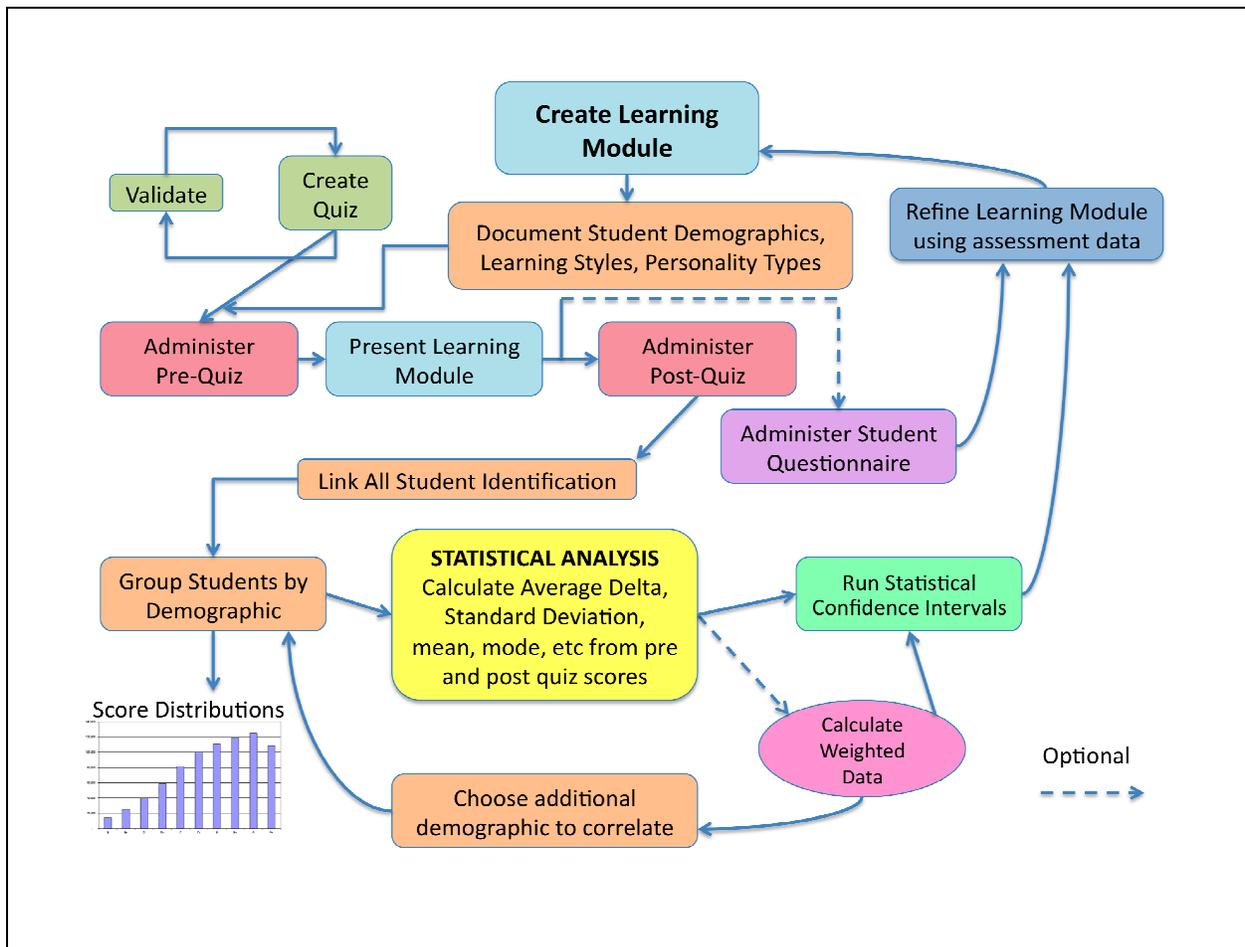


Figure 2. Equitability Correlations Assessment Method (ECAM) Algorithm

The on-line learning style and personality surveys return results indicating learning preference for the individual in each of the four categories and also includes a weight or strength for that preference. These data allow one to differentiate, for example, between someone who is only slightly “active” over “reflective” in their learning style and someone who very strongly prefers an “active” to “reflective” learning environment. The average quiz scores and change in scores (deltas) are weighted using linear interpolation according to the weights reported from the corresponding learning style or personality survey for each student. The confidence intervals are calculated across the unweighted and weighted deltas.

### Assessment Results

The tutorial assessment methodology [Fig. 2] is applied to four specific FE learning modules as representative examples from the set of tutorials developed as par to this work. Data for these modules include student demographics, learning styles, and personality types, in addition to student scores on pre- and post-quiz for each module. These four complete sets of data are used as the input to traverse the assessment algorithm in its entirety.

The assessment methodology seeks general trends in the statistical results. At the fundamental level, the quiz scores were assessed. Across all of the demographics, the pre- and post-quiz scores can be analyzed as a whole. If the entire group of students is improving in quiz scores, the FE tutorial has done its job well. The average of each group indicates an initial snapshot of the results, but only on a basic statistical distribution level.

The assessment algorithm is an iterative process, where the purpose is to continue reviewing the FE learning modules as more data are processed. Each level of evaluation, student demographics, learning styles, personality types, quiz scores, student surveys, and correlation statistics should be fed back into the evaluation of the FE tutorial learning modules and the assessment itself. If one student group in the pair of a particular personality type or learning style is performing significantly better or worse than its counterpart, the tutorial should be reviewed and modified. The goal is to equitably improve learning across student groups. This performance variance is seen in a confidence interval over 50%, explained in detail next.

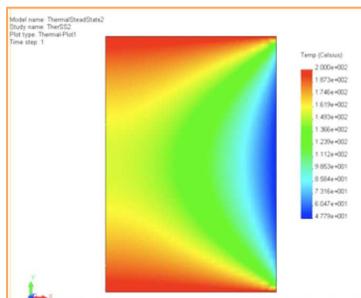
The confidence intervals represent the likelihood that the deltas for pairs of learning styles are statistically different. For example, a confidence interval of 75% for “active” vs. “reflective” learners indicates that there is a 75% likelihood that there is a real (statistically speaking) difference between the deltas for these two opposing learning styles. Although the confidence interval threshold of 95% is commonly used to indicate statistical significance, it may be informative to consider any occurrences where the confidence interval is greater than 50%. This would indicate that there was greater than 50% likelihood that one learning style benefited more than another from the FE learning module. The desirable result we are looking for is less than 50% chance that any one learning style or personality type is performing unequally to another.

The results of this project can be summarized into three broad categories in assessment of the FE learning modules: (1) Effectiveness in facilitating understanding of specific engineering knowledge and concepts; (2) Effectiveness in providing engineering students opportunities to apply commercial FE software to solve typical problems with the finite element method or finite volume method; and (3) Flexibility to meet the learning requirements of students with broad and *Learning Styles* and *MBTI Indices*.

### ***An Overview of Learning Module Results & Analyses***

Tables 3 and 4 summarize the assessment results across the four exemplar FE learning modules. A clear picture of the tutorials’ impact unfolds from these assessment results, as described below.

### ***Heat Transfer FE Learning Module Results***



The “Steady-state Heat Transfer in a Bar” tutorial sets out to reinforce the student’s knowledge of expected heat transfer results under equilibrium analysis. An introduction to the use of FE heat transfer analysis software begins the tutorial. The FE method provides a comparison to the explicit two-dimensional finite difference method presented in most heat transfer texts.

Table 3. Assessment results of learning module data across learning styles.

		Learning Style	N	Pre-quiz	Post-quiz	Delta	Stdev	Weighted Pre-quiz	Weighted Post-quiz	Weighted Delta
		FINITE ELEMENT TUTORIALS								
VIBRATIONS	Active	4	43.5	67.8	24.3	10.2	43.4	68.3	24.9	
	Reflective	3	58.3	95.3	37.0	7.2	58.3	95.3	37.0	
	Sensing	4	43.5	75.0	31.5	14.8	45.8	82.3	36.5	
	Intuitive	3	58.3	85.7	27.3	2.1	62.7	89.9	27.1	
	Sequential	1	71.0	100.0	29.0	-	71.0	100.0	29.0	
	Global	6	46.3	76.2	29.8	11.8	43.1	74.2	31.0	
<b>Average 30 Pt. Improvement</b>										
CURVED BEAM	Active	10	46.6	61.1	14.5	12.01	47.6	60.7	13.0	
	Reflective	4	69.0	78.0	9.0	9.00	86.7	89.7	3.0	
	Sensing	8	47.1	61.1	14.0	13.57	43.3	58.4	15.1	
	Intuitive	6	62.0	73.1	11.1	13.18	53.0	64.2	11.1	
	Sequential	10	55.6	67.9	12.3	11.15	59.4	70.9	11.5	
	Global	4	51.0	64.4	13.4	11.50	31.6	44.3	12.6	
<b>Only Pair with 10 Pt. Difference</b>										
<b>All &gt; 10 Pt. Improvement</b>										
STRUCTURAL STIFFNESS	Active	6	61.7	68.3	6.7	10.3	63.7	69.0	5.3	
	Reflective	5	54.0	56.0	2.0	14.8	48.5	58.5	10.0	
	Sensing	7	58.6	61.4	2.9	12.5	59.3	60.7	1.3	
	Intuitive	4	57.5	65.0	7.5	12.6	61.7	62.2	0.6	
	Sequential	5	56.0	60.0	4.0	15.2	53.3	49.3	-4.0	
	Global	6	60.0	65.0	5.0	10.5	64.0	67.0	3.0	
<b>Reflective 5 Pt. &gt; Active Sensing 1 Pt. &gt; Intuitive Global 7Pt. &gt; Sequential</b>										
HEAT TRANSFER	Active	6	61.9	61.9	0.0	12.8	60.2	60.2	0.0	
	Reflective	4	67.9	71.4	3.6	18.0	80.6	77.6	-3.1	
	Sensing	6	52.4	54.8	2.4	16.7	52.8	58.8	6.0	
	Intuitive	4	82.1	82.1	0.0	11.7	85.1	81.2	-3.9	
	Sequential	8	64.3	62.5	-1.8	11.9	61.0	60.4	-0.7	
	Global	2	64.3	78.6	14.3	20.2	53.6	75.0	21.4	
<b>Likely Just Statistical Noise</b>										
<b>~ 20 Pt. Improvement</b>										

Learning Style Differences	Unweighted Confidence Interval (%)	Weighted Confidence Interval (%)
Reflective vs. Active	87.5	86.0
Sensing vs. Intuitive	38.3	70.0
Global vs. Sequential	13.0	30.9
Active vs. Reflective	61.9	86.7
Sensing vs. Intuitive	30.1	40.9
Sequential vs. Global	12.3	12.8
Reflective vs. Active	42.6	42.6
Sensing vs. Intuitive	42.3	7.47
Global vs. Sequential	9.51	58.4
Active vs. Reflective	25.5	22.0
Sensing vs. Intuitive	20.2	69.6
Global vs. Sequential	52.4	62.2

Table 4. Assessment results of learning module data across MBTI types.

		Personality Types	N	Pre-quiz	Post-quiz	Delta	Stdev	Weighted Pre-quiz	Weighted Post-quiz	Weighted Delta
<b>FINITE ELEMENT TUTORIALS</b>	<b>VIBRATIONS</b>	Extrovert	2	65.0	70.0	5.0	7.1	61.4	70.0	8.6
		Introvert	4	59.0	93.0	34.0	8.4	57.3	92.5	35.3
		Sensor	2	59.0	93.0	34.0	7.1	47.9	86.5	38.6
		INtuitor	4	49.5	82.0	32.5	7.9	49.2	80.2	30.9
		Thinker	2	50.0	85.5	35.5	10.6	43.5	72.1	28.6
		Feeler	4	54.0	85.8	31.8	6.1	59.0	89.0	30.0
		Judger	4	59.0	93.0	34.0	8.4	60.2	94.1	34.0
		Perceiver	2	40.0	71.0	31.0	4.2	39.6	71.0	31.4
	<b>CURVED BEAM</b>	Extrovert	11	50.5	64.6	14.2	12.5	48.2	63.3	15.1
		Introvert	3	52.0	63.3	11.3	0.6	50.0	61.5	11.5
		Sensor	6	57.5	72.3	14.8	11.7	56.0	70.9	14.9
		INtuitor	7	47.6	57.1	9.6	7.6	43.8	53.6	9.8
		Thinker	10	49.9	63.4	13.5	12.8	47.3	61.4	14.1
		Feeler	4	53.0	66.8	13.8	5.5	51.0	66.1	15.1
	<b>STRUCTURAL STIFFNESS</b>	Extrovert	9	55.6	60.0	4.4	13.3	54.6	61.0	6.5
		Introvert	2	70.0	75.0	5.0	7.1	75.9	77.9	2.1
		Sensor	6	63.3	66.7	3.3	10.3	63.5	71.4	7.9
		INtuitor	5	52.0	58.0	6.0	15.2	50.9	58.2	7.3
		Thinker	5	58.0	66.0	8.0	8.4	62.4	68.1	5.7
		Feeler	6	58.3	60.0	1.7	14.7	57.1	53.1	-4.0
	<b>HEAT TRANSFER</b>	Extrovert	5	48.6	57.1	8.6	16.3	53.2	70.7	17.5
		Introvert	5	80.0	74.3	-5.7	7.8	82.8	75.6	-7.1
		Sensor	6	69.1	66.7	-2.4	10.8	66.0	63.7	-2.4
		INtuitor	4	57.1	64.3	7.1	18.4	71.6	78.3	6.7
		Thinker	5	68.6	62.9	-5.7	7.8	78.2	73.0	-5.2
		Feeler	5	60.0	68.6	8.6	16.3	56.7	70.5	13.8
		Judger	6	59.5	57.1	-2.4	10.8	53.4	47.8	-5.6
		Perceiver	4	71.4	78.6	7.1	18.4	79.2	77.9	-1.3

Personality Type Differences	Unweighted Confidence Interval (%)	Weighted Confidence Interval (%)
I vs. E	95.3	94.5
S vs. N	16.4	64.8
F vs. T	27.6	11.1
J vs. P	39.8	34.7

Personality Type Differences	Unweighted Confidence Interval (%)	Weighted Confidence Interval (%)
I vs. E	53.3	61.3
N vs. S	63.7	60.5
T vs. F	3.9	15.2

Personality Type Differences	Unweighted Confidence Interval (%)	Weighted Confidence Interval (%)
E vs. I	5.91	42.02
S vs. N	25.04	5.36
T vs. F	60.26	79.3

Personality Type Differences	Unweighted Confidence Interval (%)	Weighted Confidence Interval (%)
E vs. I	86.3	97.2
N vs. S	59.6	57.3
F vs. T	86.3	93.5
P vs. J	59.6	30.3

**Average 30 Pt. Improvement**

**10-15 Pt. Improvement**

**Extroverts & Thinkers Outperform Counterparts**

**Conducive to: Extroverts INtuitors Feelers & Perceivers**

An experimental group evaluates the Heat Transfer learning module and in this experimental set of data, all the students are visual learners. All personality types are represented in the correlation analysis. The ten students who participated in this learning module study and completed the learning style and personality tests were mostly senior engineering majors who were required to take the heat transfer course.

An overview of data from the heat transfer tutorial show that five of the six learning style groups are not performing better or worse on the post-quiz when compared to the pre-quiz. The global learning group, however, definitely improves their overall FE heat transfer understanding by at least twenty points. When it comes to comparing the results of each pair of learning styles participating in the Heat Transfer tutorial, the story is more conclusive. As reported in the weighted delta column, the active learners and reflective learners perform basically the same. Their deltas both report little to no change between pre- and post-quiz averages and is confirmed with a 22% confidence interval. Far below the 50% cutoff discussed, it can be confidently said that most likely the majority of the group is getting the same amount of help from the tutorial. The sensing learning style, however, is doing slightly better than their intuitive counterparts. The weighted confidence interval of 69% suggests that in this group the sensing students are likely learning more than the intuitive students. An interpretation is that the tutorial is written more towards sensing type learning and lacks equal weight of intuitive learning. Finally, the global learners are most likely out performing the sequential learners with a 62% confidence interval. The global learners are improving their quiz scores while the sequential learner scores stay the same.

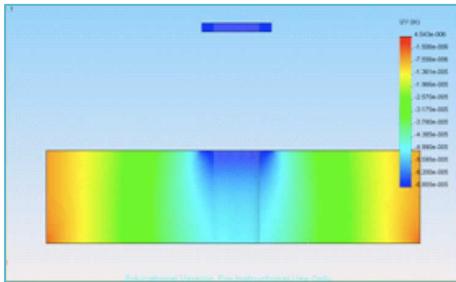
The personality type results for the heat transfer tutorial indicate that two of the personality groups are evenly split 50/50, and two are 60/40. The pre-quiz scores have a much wider range of just below 50 up to 80. The post-quiz scores have almost the same range and deltas range from losing about 5% to gaining approximately 8%. In all four personality groups, one of the pairs seems to be doing worse on the quiz after the tutorial, compared to the counter pair. Reviewing the weighted delta, this learning module is conducive to: extroverts, iNtuitors, feelers, and perceivers.

In all four cases, the tutorial appears to be biased towards one side of the personality. There is an extreme spread, 97% confidence interval, across the extrovert versus introvert group. The tutorial is likely to be very biased towards extroverts. In the next group, the intuitors are gaining more from the tutorial, but the spread is not as wide, just a 57% confidence interval. Again, the thinker versus feeler spread is quite large, with a 94% confidence interval biased towards feelers. The last group, judges and perceivers, have an unweighted confidence interval around 60%, but only 30% when the data is weighted. Whether or not this implies a biased towards perceivers, it is more significant that both groups are not improving after the tutorial.

The insights gained from this analysis are twofold, in concurrence with the goals of assessing the learning module for overall educational benefit and for equality across all learning style and personality type groups:

1. The tutorial needs to be significantly advanced to improve student learning, as seen with a minimum improvement of 10 points on the quiz
2. The tutorial is geared towards certain learning styles and personalities in most cases and should be adjusted to include all groups equally in the active learning process; however these results are not conclusive or definite since the learning module does not significantly provide for student improvements in learning.

### ***Stiffness FE Learning Module Results***



The “Bolt and Plate Stiffness” tutorial bolsters the student’s knowledge of structural stiffness concepts in bolted joint connections. Introduced to the FE software, the student can predict bolted joint stiffness for plates. Pictorially, the stiffness field in a plate under a bolt can be reviewed.

For the sample experimental group in this learning module, the same visual versus verbal learning style correlation is missing as with the heat transfer assessment. In addition, the judger/perceiver personality type could not be analyzed for this set of data. All of the students are perceivers in this case. The total number of students involved in this study was 11, all senior mechanical engineering students.

Quiz results are presented across the learning groups for the Stiffness tutorial. The raw delta scores show a slightly positive trend that is all of the learning styles improve between 2 and 7.5 points on the quiz. The standard deviations range between 10 and 15 points. Once the data is weighted, we see that the reflective group performed 5 points better than active; sensing less than 1 point better than intuitive; and global 7 points better than sequential.

We cannot tell initially if the differences in deltas, either weighted or unweighted, statistically mean the groups are likely to be performing differently. Taking the deltas, standard deviations, and corresponding group sample sizes into account, data indicate the raw delta results for this tutorial do not imply statistical difference. All of the unweighted confidence intervals fall under the 50% cutoff, so the groups are likely to be performing equally. Similarly, the weighted confidence intervals are small, with the exception of the 58% result for global versus sequential. Overall, this tutorial shows student performance equally across the three learning styles pairs involved, but is slightly favoring global learners over sequential learners.

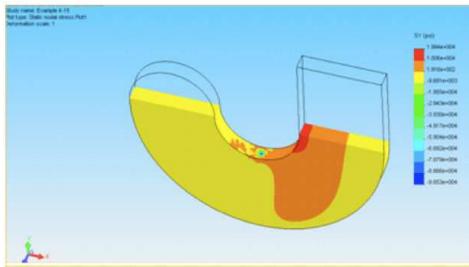
The same eleven students provide a similar story when it comes to personality types. The range of deltas is between losing 4 points and gaining 8. The standard deviations are up to 15 points again. Just considering deltas, the extroverts and thinkers outperformed their counterparts on the post-quiz. The confidence intervals need to be considered to determine if these differences are significant or not.

Both the extrovert versus introvert and sensor versus intuitor groups resulted in confidence intervals far below 50%, implying the students are most like learning equally across their

personality types. The 60% and nearly 80% unweighted and weighted confidence intervals suggest that thinker personality types are more likely benefiting more than feeler personalities.

For the stiffness tutorial, the learning module is helping students learn equally across the majority of learning styles and personality types. This assistance level needs to be improved however, as no group performed over ten points higher on the quiz after using the tutorial.

### ***Curved Beam FE Learning Module Results***



The “Curved Beam” tutorial tests student understanding of stress distributions in a curved hook using the FE software. To verify the stress distribution, the student determines the neutral axis of the curved beam numerically and graphically.

For this experimental group, the set of data show the same trends as for the Stiffness learning module; all the students are visual and perceiving. The student group sized increased to 14 in total for this senior machine design course.

The quiz average, delta, and standard deviation for each learning style for the Curved Beam tutorial. The 14 students are distributed in various combinations, but all the quiz averages are weighted with corresponding indices from the student learning style types. We can see that five out of the six groups perform over ten points higher on the quiz as a result of using the FE learning module. The only pair that shows any real difference in quiz performance is the active learners more so than reflective learners, receiving ten more points in weighted delta terms.

In the Curved Beam module data analysis, the unweighted and weighted confidence intervals for the first pair demonstrate there is between a 62% and 87% chance that the reflective learners benefit statistically different than the active learners. The last two learning style pairs benefit equally, resulting in a 11 to 15 points gain from the learning module.

All of the personality types perform better on their post-quizzes after using the Curved Beam learning module. The improvement range is between 10 to 15 points.

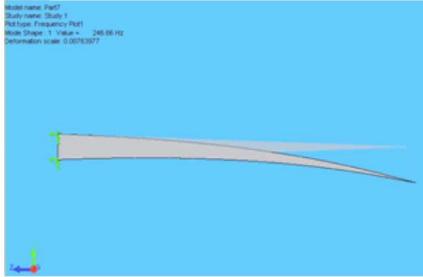
Improvements needed on the Curved Beam tutorial can be in reaction to two personality pairs that show weighted confidence intervals of about 60% suggesting some equality needs to be added across the extrovert versus introvert group, and the sensor versus intuitor group.

Overall, the Curved Beam FE tutorial gives us an example of highly positive results from learning module assessments:

1. An average improvement of at least 10 points between the pre- and post-quiz
2. Most of the confidence intervals are below 50% to imply the learning style and personality type groups are most likely performing equally with the tutorial.

Together, these results suggest this learning module is effectively reaching most students.

### ***Vibration FE Learning Module Results***



“Lateral Vibration of Tapered Cantilever” is a tutorial that takes the student through concepts including natural frequency and vibration modes in a non-uniform cantilever beam analysis. The student is introduced to the FE method by determining the beam mode shapes at resonance frequencies. With the software, these findings can be graphically verified.

For the experimental group, the final set of data includes seven senior engineering students, spread across all four personality types. The visual versus verbal learners are again absent from this experimental group.

The learning style correlation for the Vibrations module average quiz scores represents an average quiz score improvement of approximately 30 points. , Coupled with an average standard deviation of about 10, this suggests the particular tutorial used for this learning module is very effective in assisting students learn. Some groups may be outperforming their counterparts, as seen through confidence intervals, but overall this learning module is outperforming the three previous tutorials discussed.

The following groups are most likely learning unequally across learning styles: reflective may be getting more from the tutorial than active learners and sensors are performing statistically better than intuitors. These confidence intervals around 70% to 80% tell us we need to improve the learning style equality across all the learning styles.

All but the extroverted personality types are gaining an extra 30 points of knowledge on the quiz due to the Vibrations learning module. The 95% confidence interval for the introverts versus extroverts shows, with high likelihood, the introverts are learning statistically different than the extroverts. This tutorial is geared towards introverts and should be revised to assist extroverted learning equally.

In the end, this Vibrations learning module presents results that are positive. It is evident that tutorials can help students improve on their quiz over 10 points, and even up to 30 points. This result is very promising; the FE tutorials have a chance to really improve student learning. The equitability correlations give us initial feedback on how to improve the learning experience for all students, no matter their preferred learning style or personality type.

### **Discussion**

As a result of this work to date, there is much to take away from the demographic correlations of the FE learning modules. First, the tutorials are helpful as complementary lessons to topics in challenging engineering courses. They are also, at a basic level, assisting students in being introduced to the real-world FE method. The assessment results for the exemplary learning

modules demonstrate these findings, but they also show that the development of tutorials is not a trivial process. It is possible for tutorials to not add significantly to the learning of challenging material or to bias certain student groups over others. These possibilities underscore the need for appropriate and continual assessment of the learning modules as they are created and advanced.

The tutorials developed in this project form a foundation and starting point for introducing FE across engineering curricula. The associated assessment methodology provides for continuous, open feedback and improvement. This crucial FE material, which is used in practical engineering everyday, is expressed in a unique way. These tutorials can be quickly accessed and updated (for example via the web), speeding up the optimization process to a desirable degree. This process mirrors that of FE commercial software updates used by engineering firms and the instantaneous training that employees take to solve engineering problems.

An important engineering education lesson can be taken away from the learning modules and their assessment: a single assessment strategy can answer educational value questions and demographic equality questions at the same time. These two goals, for students to not only learn well but also to learn independent of their demographics and personality types, are often kept separate and analyzed by distinctive efforts. The data show these two educational goals are not mutually exclusive. If an educator focuses on developing an active learning module that reaches the spectrum of learning styles and personality types, and allows for short-term evaluation and feedback, the learning module can be reviewed and improved before the next set of students use it. This assessment methodology goes beyond basic evaluation by correlating learning style and personality type pairs to their performance. No matter how the assessment technique is adapted to fit a unique learning tool, each level of evaluation along the way can be fed back into beneficial results for learning. The system feeds itself for continual improvement and can be a model for application to many other forms of engineering educational evaluations.

From this initial study of FE tutorials, a foundation is established for assessing the effect of learning modules. A three-stage evaluation process forms the groundwork:

1. Educational Evaluation: Is the active learning module improving student learning?
2. Equality Correlation Study: Do the learning modules help all students learn independent of their demographics, learning styles, and personality types?
3. Fundamental assessment techniques of active learning: How can the learning modules and assessment methods be iteratively and continually improved to benefit engineering education on a whole?

The project set out to assess the effectiveness and equality of the FE learning modules. A fundamental contribution from this effort is an exciting new active learning assessment methodology for the engineering education community.

## **Conclusions**

Learning modules, in the form of tutorials, form the basis of our work in developing finite element techniques to support systemic engineering principles. Our initial results show that the

development of tutorials is challenging and non-trivial. However, these results also show that tutorials can have a tremendous benefit to student learning across a range of student groups.

At the core of learning module development is the ability to assess the impact on learning. We have developed an assessment strategy targeted for tutorials, but which also generalizes across active learning methods. This exploratory new technique of assessing active education has the potential to advance engineering education. By measuring students' abilities across learning styles and personality types, the equity of the learning modules may be assessed, as well as their impact in an engineering content area.

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