

## **Measuring Self-Efficacy in Engineering Courses – Impact of Learning Style Preferences**

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## **Abstract**

Self-efficacy is an important outcome of engineering education as it relates to students' feelings, thoughts, motivations and behaviors. The key element of self-efficacy construct is a self-belief in one's abilities and has been described in detail in terms of Bandura's Social Cognitive Theory. Measuring self-efficacy of students in engineering courses is an important element of evaluating the overall effectiveness of engineering education. Traditional methods of judging student learning outcomes include quizzes, homework, exams, and course projects, with a primary focus on measuring student skills. It is important that, along with mastering the skills, students should also possess self-belief that they will be able to perform required tasks with those skills. An important research question is: How should self-efficacy be measured in engineering courses? This paper addresses this question by highlighting the results of a longitudinal study conducted on students in engineering modeling and design (junior-level) courses at Arkansas Tech University. This course is selected because the teaching method is based on project-based learning activities. Using the collected data, we have analyzed the effect of learning style preference on the perception of self-efficacy. Previous research has demonstrated that students have different preferred learning styles, and they approach learning new information in different ways. Our collected data includes student responses on their learning styles, including lectures/discussions, books/related written material, video/movies/media, hands-on activities, and a hybrid method. Paired sample t-tests and one-way analysis of variance (ANOVA) are used to analyze the collected data. These methods allow us to determine any statistically significant differences between the self-efficacy scores at the start and end of the course. We also determine the impact of learning style preference on students' perception of self-efficacy. Based on the collected data, results indicated that the self-efficacy of students improved equally using project-based learning techniques, regardless of their learning style preferences.

## **Introduction**

Engineers play an important role in the modern world as they bring ideas to reality. Innovation, creativity, and the wealth of knowledge in the engineering profession are behind the rapid developments in today's services and products. The diverse range of engineering disciplines, including electrical, mechanical, civil, and chemical, means that there is bound to be one aspect of the engineering profession that will fit a prospective student's interest and will be enticing and engaging to them. With many open engineering positions in almost every discipline, engineering graduates benefit from the many career choices available to them. The engineering profession is also about dedication to problem-solving and making the world sustainable.

To prepare students in navigating the rigors of engineering programs and succeed in the engineering profession requires mastery of quantitative skills. These skills prepare students to handle data and use numerical methods for systematic analysis and design of engineering systems. The students also follow engineering design processes to identify and solve complex problems. Engineering design is purposeful and requires formulation of an explicit goal. Engineers must choose the best possible option within the constraints of time, cost, tools, and materials. It is also

a systematic and iterative process that involves planning, modeling, simulation, building, and testing prototypes.

Success in an engineering career largely depends on a thorough understanding of engineering design processes. Two of the key outcomes of engineering education are: to prepare engineering students to identify, formulate, and solve complex engineering problems, and to apply engineering design to produce solutions [1]. Traditional assessment methods including exams, quizzes, and homework assignments are primarily designed to measure the effectiveness of engineering curriculum in skill development. However, having the skills alone does not ensure that students will be successful through the engineering program, as well as in their future careers. An important element of success is to have the will and resolve to perform with the acquired skills during the curriculum. It, therefore, becomes important to measure and clearly comprehend changes in the students' resolve as they progress through the curriculum.

A very important subject in the undergraduate engineering curriculum is engineering modeling and design. Rapid technological advances, such as the internet of things (IoT), big data analytics, engineering simulation with virtual and augmented reality, and additive manufacturing, including 3D and 4D printing, have disrupted the traditional design methodology [2]. For success in design related jobs, engineers now require deep knowledge of application, adaptation, and creation of mathematical models [3-6]. Understanding of mathematical models, conventions, and procedures for the design of experiments, data collection, and simulation is essential to operate seamlessly in the multi-disciplinary technological fields [7].

To measure the effectiveness of engineering modeling and design curriculum, it is important to determine self-efficacy of students. The aim is to enable students to go through hands-on, project-based learning activities during the curriculum to develop self-belief and optimism in their competence to accomplish tasks and produce expected results. This is an important element in determining their chances of success as future engineers. In an earlier work on this subject, the authors of this paper have proposed an instrument to measure student's perception of self-efficacy in engineering modeling and design courses [8-10]. The developed instrument was used to conduct pre- and post-course surveys of students in engineering modeling and design courses at Arkansas Tech University (ATU) to collect data for analysis. This analysis helped to draw conclusions to improve pedagogy in the course.

One of the important questions asked from students in the survey was about their preferred learning style. The concept of learning style describes the change in learning based on different phases of the learning cycle. A student's learning style refers to the preferential way in which they gather, examine, interpret, organize, conclude, and store information for further use [11-15]. According to Gardner's multiple intelligences theory, students have different preferred learning styles [11]. They also follow different approaches to learning. In educational literature, the types of learning styles are defined as visual, auditory, kinesthetic, and tactile/kinesthetic. Visual learners are those who "like to read and obtain a great deal from visual stimulation." For them, lectures, conversations and oral directions without any visual backup can be very confusing [11]. Auditory learners are those who "enjoy and learn through lectures, conversations and oral directions." They are excited by classroom interactions in role-playing and similar activities. They learn best through hearing. Kinesthetic learners are those who like movement and enjoy working with tangible

objects. They prefer frequent movement around the room and learn through hands-on activities and projects [11]. In our surveys for this study, we define the learning styles as lectures/discussions, books/written material, video/movies/media, hands-on activities, collaborative group work, mixed methods, or all the above. We analyzed the collected data to measure the impact of student’s learning style preference on their self-efficacy.

Our study employed a within-subjects design to assess the perception of self-efficacy of students in engineering modeling and design courses based on their learning style preference [8]. The participants were 57 undergraduate third-year engineering students enrolled in Engineering Modeling and Design Course (ELEG 3003) during the Fall 2017, Spring 2018, and Fall 2018 semesters. ELEG 3003 is the first course focused on engineering modeling and design within the engineering curriculum and is offered in the first semester of the third year. This course is followed by ELEG 4202 (Engineering Design) during the second semester of the junior year. ELEG 4191 (Electrical Design Project-I) and ELEG 4192 (Electrical Design Project-II) are offered during the senior year of the engineering program. The course covers topics on reduction of engineering systems to mathematical models, methods of analysis using MATLAB and Simulink, interpretation of numerical results, optimization of design variables, three-dimensional Computer-aided Design (CAD), and engineering system modeling and design projects. This course is fully hands-on, providing students with opportunities to model and simulate complex engineering systems. The students are also divided in groups to undertake course projects based on real-world and industry-proposed engineering problems. The example of engineering systems for the course are drawn from various engineering disciplines. The ABET student learning outcomes for this are given in Table 1 [8]:

Table I: ABET Student Learning Outcomes

1.	Simulate engineering systems using MATLAB.
2.	Analyze the parametric data to build a system model.
3.	Advanced plotting of system responses in two and three dimensions
4.	Solution of differential equations and working with symbolic math.
5.	Statistical analysis of the data and understanding of probability and interpolation.
6.	Numerical analysis to solve system models and related calculus problems.
7.	Model-based system design and simulation with Simulink.
8.	Design of basic engineering systems using computer-aided design software.

The topics covered during the course are designed with a goal to achieve the student learning outcomes. Essential elements of the engineering design process are emphasized through hands-on learning activities and projects.

### Self-Efficacy Construct

The self-efficacy construct referred to in this paper is based on Bandura's Social Cognitive Theory [16-18]. Bandura defines self-efficacy as “the belief in one’s capabilities to organize and execute the courses of action required to produce given attainments” [17]. These beliefs affect the way people make choices, the efforts they put into completing assigned tasks, their will and resolve when difficulties arise, and their skills to cope with difficult situations. An important argument in

Bandura's construct is that self-efficacy is not about the number of skills people possess, but what they can accomplish with those skills under different situations. Bandura also identified four major processes that contribute to the development of self-efficacy beliefs [18]. These include cognitive, motivational, affective, and selection processes. More details on these processes can be found in [18]. The self-efficacy construct is very important in the context of engineering modeling and design courses that are focused on hands-on, project-based learning methods. When the students successfully go through the experience of following the engineering design process, it is important to consider that they acquire necessary skills and competencies. As they are going through the curriculum, students develop a self-belief to perform with the acquired skills [19].

## **Purpose and Research Questions**

The purpose of this study is to investigate the impact of students' learning style preferences on the perception of their self-efficacy and confidence. More specifically, we examine variation in their level of confidence based on their preferred learning styles after they are exposed to projects and hands-on class activities during the course. This methodology helps us assess the impact on their perception regarding their abilities in the engineering design process. Finally, this study also examines whether students' course grades differed based on their preferred learning styles. We address the following specific research questions:

- (1) Do project-based learning activities affect self-efficacy and confidence of students?
- (2) Do the course scores of students differ based on their preferred learning style?
- (3) Do students' self-efficacy levels differ based on their preferred learning style?

## **Measures**

The instrumentations used for this study consisted of the following items: A demographic survey and a self-efficacy assessment survey. The self-efficacy survey comprised of twenty 10-level Likert scale questions designed to assess student's self-belief in their ability to use the skills learned during the course.

### **Demographic Survey**

- The demographic survey was to collect information about the participants' makeup such as gender, ethnicity, learning style, GPA, and familiarity with the use of technology.

### **Self-Efficacy Survey**

- This survey was designed to measure the self-efficacy of students about their ability to perform a specific task at a designated level in accordance with Bandura's guidelines [17]. The survey was used twice during a semester (first week and the last week). For this instrument, the researchers used a 20-item questionnaire and suggested the possibility of three higher order factors: (a) Logical thinking skills (e.g., develop a statistical model of an engineering process, analyze data with a modeling and simulation software); (b) Communication skills (e.g., effectively communicate and document to wider audience progress through the engineering design process ); and (c) Problem Solving skills (e.g.,

work well with hands, think practically to find a solution to an engineering problem). As an example of a Likert-scale question about students' self-efficacy regarding their problem-solving skills, students were asked the following question: I can transform an analytical model into a working code to run on simulation software. Students had the choice to indicate the degree of confidence they can complete that task, where: 0 = cannot do at all, and 10 = highly certain can do. Another question example regarding students' logical thinking skills: I can redesign a prototype if it does not perform according to specifications during testing. Students had the choice to indicate the degree of confidence they can complete that task, where: 0 = cannot do at all, and 10 = highly certain can do.

The data was then screened for univariate outliers or missing values. One missing value was identified due to one student dropping the course after a few weeks. This resulted in missing data in the end of course survey. The minimum amount of data for factor analysis was satisfied, with a final sample size of 57 (using list-wise deletion), providing a ratio of over 19 cases per variable following the rule of 10, where it should be at least a minimum of 10 cases for each item in the instrument being used [20-22].

## Participants

The participants in the present study were 57 engineering students (undergraduate), enrolled in engineering modeling and design courses. Participants were science major 54 male and 3 females. English was reported as the native language of all participants. The average reported age of the participants was 18-25 years. Majority of participants were familiar with using technology and they preferred hands-on classroom activities. Table II summarizes students' descriptive statistics. It can be observed that for some learning styles (Collaborative Group Work, Books/Written Material, and Video/Movies/Media) the number of students was small. As this is a longitudinal study, researchers expect that as more data will be collected in future courses, the number of students with those learning styles will also increase.

Table II: Students' Descriptive Statistics

	Level	Counts	Total	Proportion	p
Gender	Male	54	57	0.947	< .001
	Female	3	57	0.053	< .001
Age	18-21	39	58	0.672	0.012
	22-25	12	58	0.207	< .001
	26-30	4	58	0.069	< .001
	31-40	2	58	0.034	< .001
	41 and above	1	58	0.017	< .001
Learning Style	Lectures/Discussions	7	58	0.121	< .001
	Books/Written Material	3	58	0.052	< .001
	Video/Movies/Media	3	58	0.052	< .001
	Hands-on activities	24	58	0.414	0.237
	Collaborative Group Work	1	58	0.017	< .001
	Mixed method or all the above	20	58	0.345	0.025
<b>Note.</b> Proportions tested against value: 0.5.					

## Procedure

Students in all sections completed demographic and self-efficacy surveys at the beginning of the semester. Students then attended 14-weeks class activities on engineering modeling and design such as transforming an analytical model into a working code to run on simulation software, statistical modeling of an engineering process, developing test methods to check if a prototype meets the specifications, and operating engineering tools and common workshop machinery. At the end of the semester, students completed the self-efficacy survey again.

## Results

Prior to the main analyses, data was screened for systematic patterns of missing data (e.g., when no value was stored for the variable within a variable sets). It was found that the missing values were scattered evenly across variables and groups with small number of cases and no apparent patterns or clusters emerged. After the initial screening, the data was ready for factor analysis.

## Factor Analysis

Initially, the factorability of the 20-item survey was examined. Several well-recognized criteria for the factorability of a correlation were used. Firstly, it was observed that all items correlated at least 0.3 with at least one other item, suggesting reasonable factorability. Secondly, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.855, above the commonly recommended value of 0.6, and Bartlett's test of sphericity was significant (Approx. Chi-Square = 821.551,  $p < .001$ ) (see Table III). The diagonals of the anti-image correlation matrix were also all over 0.5. Finally, the communalities were all above 0.3, further confirming that each item shared some common variance with other items. Given these overall indicators, factor analysis was deemed to be suitable for all 20 items on the survey.

Table III: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.855
Bartlett's Test of Sphericity	Approx. Chi-Square	821.551
	df	190
	Sig.	.000
<b>Note:</b> Significant at the $p < 0.001$ level		

Principal components analysis was then used to identify and compute composite scores for the underlying factors in the 20-item self-efficacy survey. Initial Eigen-values indicated that the first three factors explained 47%, 11%, and 6% of the variance respectively and the three-factor solution explained 65% of the variance. For the final stage, a principal component factor analysis of the 20-items was conducted using varimax and oblimin rotations, with three factors explaining 65% of the variance. An oblimin rotation provided the best-defined factor structure. All items in this analysis had primary loadings of over 0.5. Internal consistency for each of the scales was examined using Cronbach's alpha. The alphas were large: 0.895 for logical thinking skills (10 items), 0.816 for communication skills (6 items) and 0.843 for problem-solving skills (4 items) (See Table IV). After determining the suitability of data analysis techniques, we analyzed the data to answer the research questions.

Table IV: Reliability Statistics

Factor	Cronbach's Alpha	N of Items
Logical thinking skills	0.895	10
Communication skills	0.816	6
Problem solving skills	0.843	4

**Note:** *Correlation Cronbach's Alpha is large*

Overall, the analyses indicated that there were three underlying distinct factors (logical thinking, communication, and problem-solving skills) in the student's self-efficacy survey items. These factors were strongly internally consistent (See Table V). None of the 20 items in the survey were eliminated for this analysis. An approximately normal distribution was evident for the composite score data in the current study, thus the data was well suited for parametric statistical analyses. There was little difference between the three-factor varimax and oblimin solutions, thus both solutions were examined in subsequent analyses before deciding to use an oblimin rotation for the final solution.

Table V: Correlations between Factors

		Logical thinking	Communication	Problem-solving
Logical thinking skills	Pearson Correlation	1	0.656**	0.779**
	Sig. (2-tailed)		0.000	0.000
	N	57	57	57
Communication skills	Pearson Correlation	0.656**	1	0.597**
	Sig. (2-tailed)	0.000		0.000
	N	57	57	57
Problem solving skills	Pearson Correlation	0.779**	0.597**	1
	Sig. (2-tailed)	0.000	0.000	
	N	57	57	57

**Note:** \*\*. *Correlation is significant at the 0.001 level (2-tailed).*

**First Question:** Do project-based learning activities affect self-efficacy and confidence of students?

To answer the first question, we conducted paired samples t-test to compare students' mean of self-efficacy before and after teaching the course with a hands-on, project-based method. Results of the paired-samples t-test show that mean self-efficacy at the beginning of the course ( $M = 1303$ ,  $SD = 309.8$ ) and at the end ( $M = 1636$ ,  $SD = 221.9$ ) at 0.001 level of significance ( $t = 12.00$ ,  $df = 56$ ,  $n = 57$ ,  $p < .001$ , 95% Confidence Interval (CI) for mean difference 337.193,  $SD = 212.096$ , Paired Samples Correlation  $r = 0.73$ ). On average students' self-efficacy increase was about 337.193 points at the end of the course.

As displayed in Table II, there are statistically significant differences, at the 0.001 significance level, between the self-efficacy scores at the beginning and end of the courses. Tables VI, and VII



summarize descriptive statistics from paired-samples t-tests performed for the same groups of participants. The plot of self-efficacy scores before and after the course is given in Fig. 1.

Table VI. Paired Samples Descriptive Statistics

	N	Mean	SD	SE
Self-Efficacy After	57	1636	221.9	29.39
Self-Efficacy Before	58	1303	309.8	40.68

Table VII: Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Self-Efficacy After & Self-Efficacy Before	337.193	212.096	28.093	280.916	393.470	12.003	56	.000

**Note.** For the Student t-test  $p < 0.001$

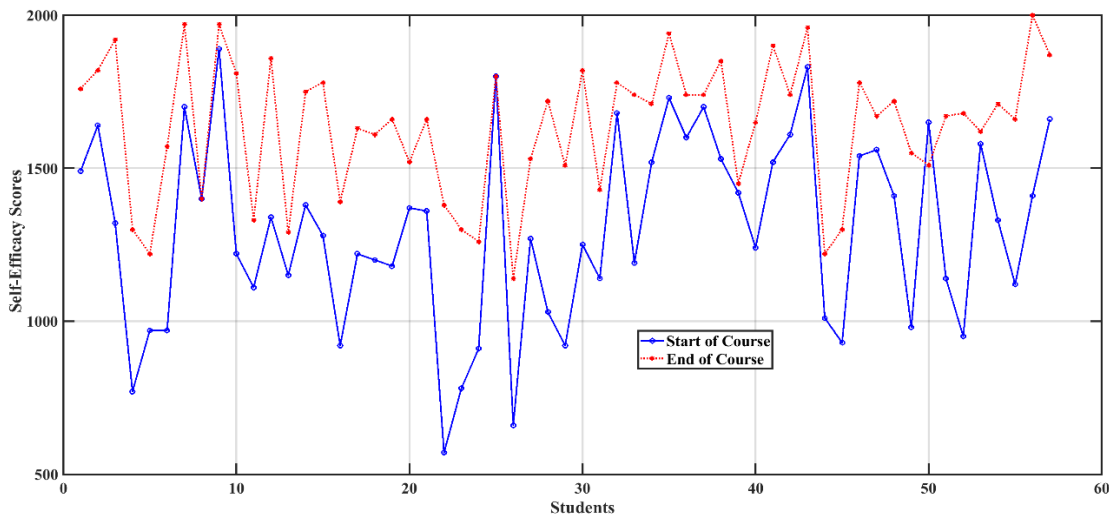


Figure 1: Pre and Post Course Self-efficacy Scores.

**Second question:** Do the students' course scores differ based on their preferred learning style?

To answer this question, the researchers conducted a one-way between subjects' ANOVA to compare the effect of project-based learning methods on students' course grades based on their learning styles. The results of the analysis indicate that students' course grades did not differ based on their learning style. Comparisons between students indicated that the mean scores for all learning styles weren't different from each other. Table VIII summarizes the one-way between subject's ANOVA.

Table VIII.

One-way between subjects' ANOVA to compare the effect of project-based learning methods on students' course grades based on learning style

Cases	Sum of Squares	df	Mean Square	F	p
Learning Style	1228	5	245.6	1.364	0.253
Residual	9184	51	180.1		

**Note.** Type III Sum of Squares. Significant at  $p < .001$

**Third question:** Do students' self-efficacy levels differ based on their preferred learning style?

To answer this question, the researchers conducted a one-way between subjects' ANOVA to compare the effect of project-based learning methods on students' self-efficacy based on their learning style. The results of the analysis indicate that students' self-efficacy level did not differ based on their learning style.

Comparisons between students indicated that students' total self-efficacy mean scores and all sub-skills (Logical thinking skills, Communication skills and Problem-solving skills) for all learning styles weren't different from each other. Tables IX-XII summarize the one-way between subject's ANOVA.

Table IX

One-way between subjects' ANOVA - Effect of learning style on total Self-efficacy scores

Cases	Sum of Squares	df	Mean Square	F	p
Student's total Self-efficacy	105.14	40	2.629	0.836	0.688
Residual	50.33	16	3.146		

**Note.** Type III Sum of Squares. Significant at  $p < .001$

Table X

One-way between subjects' ANOVA - Effect of learning style on self-efficacy in logical thinking skills

Cases	Sum of Squares	df	Mean Square	F	p
Logical thinking skills	69.11	29	2.383	0.745	0.781
Residual	86.37	27	3.199		

**Note.** Type III Sum of Squares

## Conclusion

We presented results of a longitudinal study to analyze the impact of learning style preferences on self-efficacy of students in engineering courses. This subject is very important for engineering students, as a thorough understanding of engineering design processes is essential to a successful engineering career. We also focused on analyzing factors that can predict student performance in the course based on their confidence and self-efficacy. Three key factors that play an important

role in student performance are logical thinking skills, communication abilities, and problem-solving skills. This study was conducted over three semesters and was comprised of 57 undergraduate students. We used a 20-question Likert scale instrument to survey students at the beginning and end of the course to collect data for analysis.

Based on extensive statistical analysis of the collected data, the answers to research questions were presented in the study. The data was initially screened to identify any systematic patterns of missing variable values. It was found that the missing values were evenly scattered across variables. We performed a factor analysis on the collected data using several well-recognized statistical approaches to identify suitable techniques for data analysis. We used paired sample t-tests and one-way analysis of variance to analyze the data with respect to the research questions. The results indicate that students' self-efficacy scores improved after going through hands-on, project-based learning activities during engineering modeling and design courses. The analysis also indicates that logical thinking, communication, and problem-solving skills are significant predictors of students' performance in the course. The results also showed that students' self-efficacy scores did not differ based on their preferred learning styles. This indicated that the teaching approach using projects and hands-on activities was equally effective for all students, regardless of their preferred learning styles. We plan to continue this study in the coming semesters to collect more data and analyze it to identify particular hands-on activities that can significantly impact self-efficacy scores of students.

Table XI

One-way between subjects' ANOVA - Effect of learning style on self-efficacy in communication skills

Cases	Sum of Squares	df	Mean Square	F	p
Communication skills	61.39	24	2.558	0.870	0.634
Residual	94.08	32	2.940		

Note. Type III Sum of Squares

Table XII

One-way between subjects' ANOVA - Effect of learning style on self-efficacy in problem solving skills

Cases	Sum of Squares	df	Mean Square	F	p
Problem solving skills	59.24	18	3.291	1.299	0.242
Residual	96.24	38	2.533		

Note. Type III Sum of Squares

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