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Active Learning in Engineering Graphics: An Analysis of Self-Efficacy for At-Risk and Not At-Risk Students

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Abstract

Part of a more extensive National Science Foundation-funded study, this study presents the findings and analysis of the effect on three-dimensional modeling self-efficacy (3DSE) by the inclusion of online active learning modules (ALM). Using multiple datasets, we found that the use of ALM in an introductory engineering graphics course, closed a gap in 3DSE scores between majority and minority students, populations historically underrepresented in engineering. Although limited to a single university, the results support that the inclusion of active online learning may address an important construct known to be a factor in academic success and persistence in engineering.

Introduction

Nationally, less than 30% of students who initially matriculate into undergraduate engineering programs complete them within 4 years, with 54% completing in six or fewer years (Yoder, 2012). Even with a plethora of research and programmatic initiatives, there continues to exist an issue with retention and persistence in university engineering programs.

As a discipline, engineering graphics courses are a fundamental component of many engineering programs of study. Frequently, engineering graphics courses are an opportunity to reach a broad swath of engineering students from a variety of majors within an engineering context rather than common mathematics or science courses. This context situates engineering graphics courses in a unique position for educational interventions to potentially affect higher numbers of students than in any other domain within engineering education. This is especially true if the intervention, or assessment of its effect, requires it take place within an educational context.

The study reported in this paper examined one such domain-specific construct assessment, three-dimensional modeling self-efficacy (3DSE). This paper is the first in a series of assessments and interventional study analyses intended to increase academic outcomes and non-cognitive factors related to persistence in engineering education. This large, multi-institution ongoing thematic research study, supports the development, implementation, and refinement of online active learning modules (ALM). In this paper, we detail the first-year pilot study and the changes in 3DSE over the semester-long ALM inclusion in the course.

Theoretical Framework

Self-efficacy is a person's confidence in his or her ability to muster the necessary intrinsic resources for successful task completion (Stajkovic & Lu-

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thans, 1998). More simply put, self-efficacy can be described as: "people's judgments of their capabilities…" (Bandura, 1986), p. 391), and those are central to personal agency (Bandura, 1989; Lent, Brown, & Hackett, 1994). Self-efficacy is a known mediator of behavior which influences the academic performance of a student (Lent, Brown, & Larkin, 1984). Along with research supporting the mediation effect of self-efficacy beliefs on academic performance and goal attainment, researchers have found self-efficacy also mediates academic effort, persistence, and perseverance (Pajares, 1997). Self-efficacy has also been shown to be positively associated with performance among introductory engineering graphics students (Denson, Kelly, & Clark, 2018; Kelly, 2017; Metraglia, Baronio, & Villa, 2015; Metraglia, Villa, Baronio, & Adamini, 2016).

Self-efficacy is known to be domain and task-specific and is not considered to apply to general topics and subjects, but rather, considerably more specific judgments about one's capabilities (Linnenbrink & Pintrich, 2003). The specificity of self-efficacy measures is an important consideration as self-efficacy is a predictive factor for student performance (Zimmerman, 2000). For these reasons, the domain-specific 3DSE instrument was developed and tested (Denson, Kelly, & Clark, 2018; Kelly, 2017).

It is important to note that the broader research to which this study pertains discusses engineering education persistence generally; however, the assessment measures the concepts with an engineering graphics education. To address this, we rely on prior research that demonstrated that self-efficacy trends found in engineering generally also exist and are consistent within engineering graphics (Denson, Kelly, & Clark, 2018). In particular, Kelly (2017) found that although scoring significantly higher on academic achievement measures, female students had significantly lower self-efficacy levels. This is consistent with engineering education, as was the percentage of students' final grade variance described by their self-efficacy levels. This consistency with engineering generally, the variety of engineering majors who take engineering graphics courses, and the consistent construct (three-dimensional modeling) found in most engineering graphics courses, allowed for the findings to be more generalizable to engineering education.

Contextualization

This study is part of a broader NSF grant-supported research project that examines the effect of the use of online ALM on both cognitive and non-cognitive factors related to achievement and persistence such as self-efficacy, motivation, spatial acuity, grades, and interview responses. The present study population is undergraduate engineering graphics students at a large, engineering-focused public university in the southeast United States. The course is taught in large class sections (~60 students per section), five to six sections per semester, with an instructor and one or two undergraduate teaching assistants. Table 1 displays the demographics of the participants of the year one pilot. The courses follow a blended or flipped instructional model with class primarily reserved for lecture and practice. Out of class work consists of technical videos with activities, online quizzes based on the textbook and lecture notes, and work on longer-term assignments such as the final project.

Online Active Learning Modules

The ALM are provided to the students through links within the course learning management system (LMS). The ALM are broken into 10 topics representing significant themes common to engineering graphics courses and textbooks and were made to students when the topics in class were covered. Students typically had 2 weeks to complete the ALM with each one worth .5% of their final grade.

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Table 1
Demographics of Year One Pilot Study.

	All Students	Female	Male
Total	276	206	68
Race/Ethnicity			
White	208	40	166
Asian	23	7	16
Native Hawaiian or Other Pacific Islander	17	3	14
Hispanic or Latino	12	8	4
Black or African American	9	7	2
Mixed Ethnicity	5	1	4
Other Ethnicity	2	2	0
American Indian or Alaska Native	0	0	0
Academic Status			
Freshman	168	36	132
Sophomore	54	17	35
Junior	27	12	15
Senior	23	3	20
Other	3	0	3
Age (Mean in years)	19.37	18.53	19.65
Standard Deviation	3.34	3.60	3.23
GPA (Mean)	3.37	3.34	3.39
Standard Deviation	.53	.59	.50
First-generation college students	46	8	37
One or both parents are engineers	68	17	50
Registered with disability services	15	3	13
Major			
Engineering	196	48	148
Other STEM	52	9	43
Non-STEM	13	9	4
Undeclared	15	2	11

Note: Some totals may not be equal to the sum of subgroups as some participants chose not to answer.

The ALM topics are:

1. Sketching and Text,
2. Engineering Geometry,
3. Orthographic Projection,
4. Pictorial Projection,
5. Working Drawings,
6. Dimensioning – Standards;
7. Dimensioning – Annotations;
8. Assemblies;
9. Section Views; and
10. Auxiliary Views.

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The pilot ALM were developed as a series of web pages written in HTML, PHP, and JavaScript with a MySQL database backend for tracking use metrics. The ALM are housed on a secure Linux-based commercial server. Figure 1 shows a sample of an ALM page with some dynamic features that allow the student to see the shape that would be created for a revolved feature. This type of imagery allows the student to contextualize the operations used in three-dimensional solid modeling software to a real-world object with which they are more likely to be familiar.

Sketching and Text

ALM use is tracked with cookies stored in the user's browser and regular connection to the database. The database records the student's user ID, name, and the start and completion dates and times for each assigned module. The user IDs are used to Connect module use data with demographic information, cognitive and noncognitive assessments, and academic outcomes.

Instrumentation

For the study, students were given the three-dimensional modeling self-efficacy (3DSE) instrument as both a pre-and a post-test. This instrument has been shown to have predictive validity for students' final project, exam, and course grades with a population of students similar to those of the study (Denson, Kelly, & Clark, 2018; Kelly, 2017). The 3DSE is an 8-item 100-point Likert-style assessment (see Denson, Kelly, & Clark, 2018) that was given online along with assessments for motivation and spatial acuity as well as demographic information collection. In a prior study, the three-dimensional self-efficacy levels at the end of a course were significantly lower for female engineering graphics students than their male counterparts, even though females tended to have higher grades on academic measures (Denson, Kelly, & Clark, 2018).

Several demographic and background data points were collected in the survey instrument to compare the effect of the use of the ALM on 3DSE among different sub-groups. These demographic and background data points include gender, age, race, grade level, major, and current GPA.

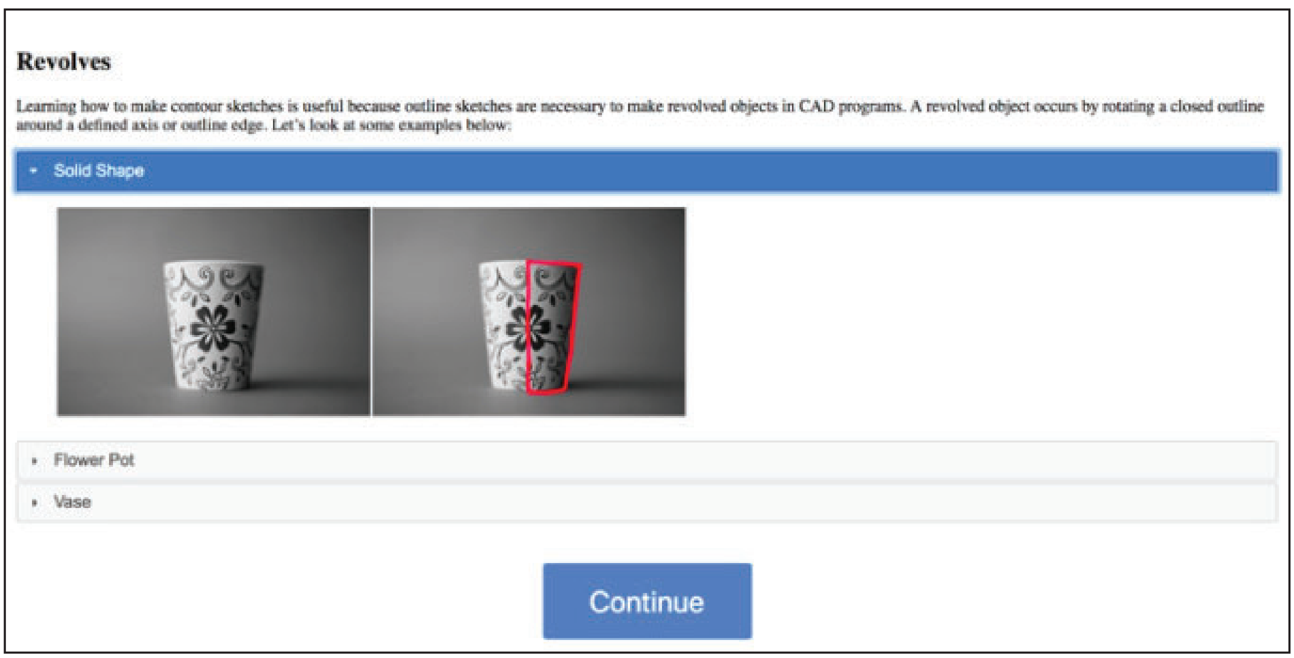

Figure 1. Example of an ALM page.

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Pilot Study Findings

The 3DSE pre-test was administered at the beginning of the semester before the start of instruction. The post-test was administered at the end of the semester, after instruction and before the final exam. Tables 2 and 3 display summary statistics by sub-group and the difference between the sub-group means and the total population means for each test.

Table 2

3DSE Pre-Test Summary Statistics by Sub-Group.

	n	Mean	SD	Diff from Total Mean
Total	276	51.55	26.30	
Gender				
Male	206	56.38	25.58	4.83
Female	68	36.47	22.99	-15.08
Race/Ethnicity				
White	208	55.49	26.41	3.94
Black or African American	9	37.64	28.82	-13.91
Asian	23	43.91	20.61	-7.64
Hispanic or Latino	12	34.41	24.02	-17.14
Mixed Ethnicity	5	47.75	18.99	-3.80
Native Hawaiian or Other Pacific Islander	17	35.28	20.87	-16.27
Other Ethnicity	2	42.94	22.36	-8.61
Major				
Engineering	196	50.67	24.59	-0.88
Other STEM	52	61.27	27.81	9.72
Non-STEM	13	34.87	32.40	-16.68
Undeclared	15	43.69	27.60	-7.86
Academic Status				
College Senior	23	37.38	23.67	-14.17
College Junior	27	46.61	27.02	-4.94
College Sophomore	54	52.00	26.09	0.45
College Freshman	168	54.24	26.07	2.69
Other	3	43.96	36.1	-7.59
GPA				
4.0+	33	41.70	22.87	-9.85
3.50-3.99	110	55.67	25.78	4.12
3.0-3.49	84	51.71	27.26	0.16
2.50-2.99	34	45.22	27.32	-6.33
2.0-2.49	11	63.67	15.09	12.12
< 2.0	4	36.37	34.08	-15.18
First-generation college students				
Yes	46	49.64	28.08	-1.91
No	227	51.95	25.92	0.40

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Table 3

3DSE Post-Test Summary Statistics by Sub-Group.

	n	Mean	SD	Diff from Total Mean
Total	276	73.09	19.5	
Gender				
Male	206	73.22	18.76	0.13
Female	68	72.2	21.8	-0.89
Race/Ethnicity				
White	208	72.58	19.19	-0.51
Black or African American	9	82.62	20.67	9.53
Asian	23	73.42	20.52	0.33
Hispanic or Latino	12	71.59	29.37	-1.5
Mixed Ethnicity	5	75.8	9.57	2.71
Native Hawaiian or Other Pacific Islander	17	72.32	16.11	-0.77
Other Ethnicity	2	87.44	17.77	14.35
Major				
Engineering	196	72.69	20.18	-0.4
Other STEM	52	74.23	15.13	1.14
Non-STEM	13	69.14	26.63	-3.95
Undeclared	15	77.63	17.71	4.54
Academic Status				
College Senior	23	73.3	14.13	0.21
College Junior	27	69.77	20.67	-3.32
College Sophomore	54	74.7	21.13	1.61
College Freshman	168	73.17	19.62	0.08
Other	3	64.29	13.27	-8.8
GPA				
4.0+	33	70	22.34	-3.09
3.50-3.99	110	73.37	18.2	0.28
3.0-3.49	84	73.55	19.91	0.46
2.50-2.99	34	76.18	17.19	3.09
2.0-2.49	11	66.02	25.9	-7.07
< 2.0	4	74.03	25.76	0.94
First-generation college students			37	
Yes	46	72.54	21.1	-0.55
No	227	73.09	19.16	0

To examine whether the differences between the pre- and post-test 3DSE scores were significant, 2-tailed paired-samples t-tests were conducted for each subgroup and the total population. Significant differences were found between most of the subgroups and the total participant group and are displayed in Table 4.

Although significant differences exist between the pre- and post-test 3SDE scores, we ac-

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knowledge that there was a full-semester engineering graphics course taught between the two 3DSE assessments. This provides some evidence that the course significantly improves the 3DSE scores of the majority of the students enrolled with a total group mean score increase of 21.54%. Many subgroups have small sample sizes, making the detection of meaningful differ-

Table 4
3DSE T-Test Results by Sub-Group.

		Paired T-Test (2-Tailed)			
	n	**Diff**	***df***	***t***	***p-value***
All	276	**21.54**	275	11.16	<.001
Gender					
Male	206	**16.84**	205	7.83	<.001
Female	68	**35.73**	67	9.18	<.001
Race/Ethnicity					
White	208	**17.09**	207	7.82	<.001
Black or African American	9	**44.98**	8	3.21	0.012
Asian	23	**29.51**	22	5.92	<.001
Hispanic or Latino	12	**37.18**	11	3.29	0.007
Mixed Ethnicity	5	28.05	4	2.3	0.083
Native Hawaiian or Other Pacific Islander	17	**37.04**	16	5.74	<.001
Other Ethnicity	2	**44.5**	1	13.7	0.046
Major					
Engineering	196	**22.02**	195	10.09	<.001
Other STEM	52	**12.96**	51	2.9	0.006
Non-STEM	13	**34.27**	12	2.59	0.024
Undeclared	15	**33.94**	14	4.49	<.001
Academic Status					
College Senior	23	**35.92**	22	6.17	<.001
College Junior	27	**23.16**	26	3.25	0.003
College Sophomore	54	**22.7**	53	5.15	<.001
College Freshman	168	**18.93**	167	7.77	<.002
Other	3	20.33	2	1.2	0.353
GPA					
4.0+	33	**28.3**	32	5.82	<.001
3.50-3.99	110	**17.7**	109	5.9	<.001
3.0-3.49	84	**21.84**	83	5.91	<.001
2.50-2.99	34	**30.96**	33	6.14	<.001
2.0-2.49	11	2.35	10	0.26	0.804
< 2.0	4	37.66	3	1.77	0.174
First-generation college students					
Yes	46	**22.9**	45	5.21	<.001
No	227	**21.14**	226	9.78	<.001

Note. Differences in bold are significant at the .05 level or lower.

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ences difficult at best. Noteworthy, however, is that the gains are substantially greater for some subgroups than for others. Table 5 displays the differences, by subgroup, of the subgroup mean score change and the total population mean score change. Many of the subgroups historically considered at-risk for persistence in engineering demonstrate greater gains than those subgroups historically represented overrepresented in engineering, white males.

Table 5

Differences from the Total Population Mean Pre/Post 3DSE Score Change.

	n	Difference	Difference from Mean(21.54)
Total	276	21.54	0
Gender			
Male	206	16.84	-4.7
Female	68	35.73	**14.19**
Race/Ethnicity			
White	208	17.09	-4.45
Black or African American	9	44.98	**23.44**
Asian	23	29.51	**7.97**
Hispanic or Latino	12	37.18	**15.64**
Mixed Ethnicity	5	28.05	6.51
Native Hawaiian or Other Pacific Islander	17	37.04	**15.5**
Other Ethnicity	2	44.5	**22.96**
Major			
Engineering	196	22.02	**0.48**
Other STEM	52	12.96	-8.58
Non-STEM	13	34.27	**12.73**
Undeclared	15	33.94	**12.4**
Academic Status			
College Senior	23	35.92	**14.38**
College Junior	27	23.16	**1.62**
College Sophomore	54	22.7	**1.16**
College Freshman	168	18.93	-2.61
Other	3	20.33	-1.21
GPA			
4.0+	33	28.3	**6.76**
3.50-3.99	110	17.7	-3.84
3.0-3.49	84	21.84	**0.3**
2.50-2.99	34	30.96	**9.42**
2.0-2.49	11	2.35	-19.19
< 2.0	4	37.66	16.12
First-generation college students			
Yes	46	22.9	**1.36**
No	227	21.14	**-0.4**

Note. Differences in bold are significant at the .05 level or lower and positive.

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The greater gains in 3DSE scores can be explained by the pre-test scores being consistently lower for particular subgroups, which is consistent with self-efficacy research pertaining to underrepresented groups in engineering education (see Kelly, 2017; Ernst, Bowen, & Williams, 2016). The post-test 3DSE scores for the pilot study show significantly larger gains for female and minority students (racial subgroups historically underrepresented in engineering) than their male and majority (students who identify as White or Asian) counterparts. There is also evidence that the subgroups regress to the mean 3DSE score between the pre- and post-tests as the interquartile ranges become smaller with the exception of the lower quartile to minimum values, which increases in the post-test by 10.13 points (excluding outliers). As can be seen in Figure 2, the pre-test has a greater variance (691.73) and a more normal distribution (skewness = -.13) of scores than does the post-test with the post-test starting to positively skew (-1.01) as the average scores approach the ceiling of 100 while the variance is reduced (380.33).

This apparent regression to the mean, although noteworthy, only describes the change in the students' 3DSE scores holistically. To understand the effect of the course and use of the ALM among subgroups, we compared the subgroup 3DSE mean scores for both pre- and post-tests to determine if significant differences existed between them.

To determine whether there were significant differences between the mean 3DSE scores between male and female students, independent-samples t-tests were conducted for both

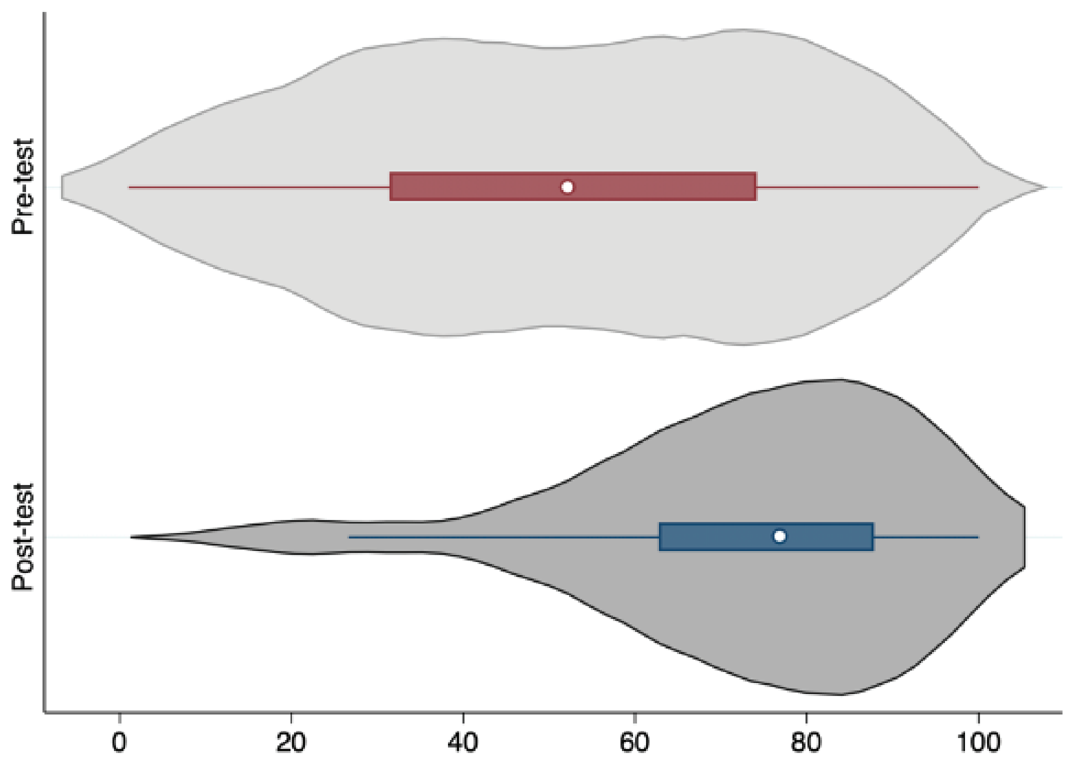

Figure 2. Violin plot for the 3DSE scores in the pilot study displaying the median, inter-quartile range, 95% confidence interval, and rotated kernel density.

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the pre-and post-tests. There were statistically significant differences between male students' 3DSE scores (M=56.38, SD=25.58) and female students' scores (M=36.47, SD=22.99); $t(272)=5.70$, $p = <.001$. No statistically significant differences exist between male (M=73.22, SD=18.76) and female (M=72.20, SD=21.80) students' 3DSE scores for the post-test; $t(272)=.37$, $p = .710$. This lack of a statistically significant difference is coupled with only a 1.02-point difference between the two groups. Given the original difference of 19.91 points, there exists no meaningful difference between genders on the 3DSE post-test.

Similarly, to determine whether there were significant differences between the mean 3DSE scores between majority and minority students, independent-samples t-tests were conducted for both the pre-and post-tests. There were statistically significant differences between majority students' 3DSE scores (M=54.19, SD=25.95) and minority students' scores (M=35.93, SD=); $t(274)=4.18$, $p = <.001$. No statistically significant differences exist between majority (M=72.73, SD=19.12) and minority (M=75.18, SD=21.76) students' 3DSE scores for the post-test; $t(274)=.73$, $p = .465$. The 3DSE scores for minority students were 18.26 points lower than the majority students' pre-test scores and were 2.44 points higher than majority students on the post-test.

The lack of significant differences on the 3DSE post-test indicates that the course with the inclusion of the ALM has effectively negated the gender and racial majority/minority differences for the construct of 3DSE among this population of students in this study.

The results of this analysis for the pilot study 3DSE data strongly suggest that the course with integrated ALM reduces or eliminates the 3DSE gaps that exist at the beginning of the course. However, based on the methods employed for the collection of this data and the interventional methods employed in this study generally, it is impossible to determine whether the changes in 3DSE are a result of the course, the addition of the ALM, or both. To address this, we compared the results of the pilot study of ALM integration to the results of baseline study data collected before the use of the ALM to investigate the differences the ALM have on student 3DSE.

Comparison to 3DSE Baseline Data

As part of a more extensive study conducted before the ALM project, a study was conducted at the same university and course as the study detailed in this paper (Kelly, 2017). The course material, delivery, and demographic makeup were not altered between the two studies. The previous study was conducted over 2 years and included the 3DSE instrument. Kelly (2017) collected post-test only data to examine the psychometric properties of the 3DSE instrument, compare student 3DSE levels with academic outcomes, and compare gender differences in 3DSE levels among engineering students. The dataset was provided for this study and used to compare the post-test 3DSE scores in this study to investigate if there were significant differences between the results to attempt to determine what, if any, effect the ALM had on student 3DSE. Table 6 displays the summary statistics by sub-group and the difference between the sub-group means and the total population mean for the original baseline dataset.

There is an approximately 6-point difference between the total group mean scores for both datasets. This is likely due to changes made to the scaling of the 3DSE between the two studies. In order to increase both the accuracy and sensitivity of the 3DSE, the instrument was changed from a 7-point Likert scale to a 100-point scale pursuant to recommendations made by Bandura (2006) for self-efficacy scale development. The data represented in Table 6 was transformed for comparative purposes, but since the 3DSE scores are not being compared directly, this transformation has no bearing on the methods used. Instead, we performed the same means testing

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Table 6

Baseline Study 3DSE Post-Test Summary Statistics by Sub-Group.

	n	Mean	SD	Diff from Total Mean
Total	717	79.28	13.46	
Gender				
Male	579	80.72	12.71	1.44
Female	128	72.8	14.95	-6.48
Race/Ethnicity				
White	533	79.41	15.79	0.13
Black or African American	19	74.62	13.72	-4.66
Asian	79	76.13	13.67	-3.15
Hispanic or Latino	29	80.91	12.35	1.63
American Indian or Alaska Native	4	70.98	4.46	-8.30
Native Hawaiian or Other Pacific Islander	4	70.09	16.06	-9.19
Other Ethnicity	24	76.41	15.79	-2.87
Major				
Engineering	584	80.21	12.48	0.93
Other STEM	95	76.05	15.49	-3.23
Non-STEM	16	61.05	20.75	-18.23
Undeclared	21	82.23	11.99	2.95
Academic Status				
College Senior	48	75.6	17.51	-3.68
College Junior	105	78.47	15.11	-0.81
College Sophomore	270	78.51	28.57	-0.77
College Freshman	288	80.79	12.15	1.51
Other	5	88.21	12.22	8.93
GPA				
4.0+	128	80.32	12.95	1.04
3.50-3.99	247	79.68	12.97	0.4
3.0-3.49	224	78.52	13.83	-0.76
2.50-2.99	99	78.64	14.39	-0.64
2.0-2.49	19	79.51	14.6	0.23

used for the pilot study data to determine if statistically significant differences exist between demographic subgroups historically underrepresented in engineering.

We performed an independent-samples t-test to compare the 3DSE levels between male and female as well as majority and minority students in the baseline study. There were significant differences in 3DSE scores by gender with males scoring 7.93 points higher on average; $t(705)=6.17$, $p = <.001$. Minority students scored significantly less on the 3DSE instrument (M=76.95, SD=13.40) than did their majority peers (M=80.09, SD=13.40); $t(715)=2.74$, $p = <.006$.

The results of the statistical analysis of both studies and the comparison to one another suggest

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that the inclusion of the ALM in the course is a contributing factor to the overall 3DSE of demographic subgroups historically considered at-risk for persistence in engineering. The statistically significant differences between these groups in the baseline study and the lack of difference in the pilot study in the absence of any structural or instructional change to the course provide evidence to support an assertion that the inclusion of the ALM may substantially aid in the closing of a demographic gap in engineering education within the context of 3DSE.

Limitations

Although the results of this study related to 3DSE on the incorporation of ALM in an introductory engineering graphics course are remarkable, there are several limitations to the study that limit the generalizability of the results. The intervention was conducted at a single, large university with an average unweighted high school GPA of 3.75. We acknowledge that randomly selected treatment and control groups would have been preferable to using the baseline study data, the structure of the course, classes, and overall research project methodology precluded this as an acceptable method. The scope of the study reported in this manuscript is also not a comprehensive accounting of all the potential variables that may have impacted student 3DSE scores.

Conclusion

This study found evidence to suggest the incorporation of the ALM in an introductory engineering graphics course had a profound effect on the 3DSE of students historically underrepresented in engineering. In prior studies and under pre-test conditions, significant differences in 3DSE were observed between underrepresented students and their majority counterparts in favor of majority students. This gap is both statistically and practically non-existent under for the pilot study participants under post-test conditions after interacting with the ALM in addition to coursework. The inclusion of the baseline data and comparison to the pilot test results suggest that, although the course material and instruction play a significant role in the 3DSE of students, the inclusion of the ALM has the potential to further diminish the gap in 3DSE among this population of students.

Future Work

As part of a more extensive study that conducted surveys measuring several constructs related to success in engineering education, the collection of demographic information, grades, and ALM completion, as well as qualitative interviews, this research is far from complete. Analysis of the other constructs and other metrics in addition to 3DSE need to be performed to get a more complete picture of the effect of the ALM in this setting. The transferability of the ALM to other institutions is also necessary to determine their full potential as a supplement to engineering graphics curricula. Although the results from this pilot show a significant increase in 3DSE for the populations examined, significant changes to the platform are currently underway to improve usability, accessibility, and greater user access metrics. Determining the reasons the ALM had the impact they did will allow instructional designers, faculty, and researchers to determine the best way to incorporate ALM into different disciplines and curricula.

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