A Comparative Analysis of the Students' Performance in two Statics Courses due to the Inclusion of an Adaptive Learning Module (ALM) to Review the Mathematics Pre-requisite Knowledge.

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Dr. Zaurin obtained his Bachelor Degree in Civil Engineering from 'Universidad de Oriente' in Venezuela in 1985. In 1990 he earned a MSc in Information Technology. He has been civil engineering professor with teaching experience at his Alma Mater (Universidad de Oriente) from 1986 until 2002. Dr. Zaurin moves to USA and completes another MSc, this time Structural and Geotechnical Engineering. Upon completing multidisciplinary PhD on Structural Health Monitoring Using Computer Vision, he joined UCF in 2010 as a Lecturer at the Civil, Environmental and Construction Engineering (CECE) Department. He has published computer vision related research work in prominent journals and still mentors graduate students in this particular area. Dr. Zaurin has been very active in the STEM area as he is one of the selected faculty members for the NSF funded EXCEL and NSF funded COMPASS programs at UCF. Dr. Zaurin received College Excellence in Undergraduate Teaching Award in 2015 and 2019, TIP Award in 2016, and also received 4 Golden Apple Awards for Undergraduate Teaching for a record four years in a row. During Fall 2013 he created IDEAS (Interdisciplinary Display for Engineering Analysis Statics) which is a project based learning activity designed specifically for promoting creativity, team-work, and presentation skills for undergraduate sophomore and junior students, as well as by exposing the students to the fascinating world of scientific/technological research based engineering. IDEAS is becoming the cornerstone event for the sophomore engineering students at UCF: from fall 2013 to fall 2018 approximately 3000 students have created, designed, presented, and defended around 900 projects and papers.

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ABSTRACT

Engineering Statics professors usually complain that students enrolled in their courses do not have the adequate mathematical knowledge they should have acquired in the pre-requisite classes. Even though they were previously tested and approved those topics, now for no apparent reason they either do not remember or cannot make adequate connections between the pure mathematical formulas and their engineering application. The implication is the students fail not in the new course concepts but in the same math topics they previously "learned". This situation has become even more acute in recent years especially due to the increase in the number of students being transferred to the university from several other institutions as well as for the variability in the background knowledge and non-uniformity in the mathematics pre-requisite coverage. Consequently, it has become even more important to start the Statics course from a common ground regarding the students' mathematical required prior knowledge.

This paper presents the results of a study that incorporated an Adaptive Learning Module (ALM) in Statics, to review such pre-required math concepts. Two sections were taught in the same manner by the same instructor, the only difference was the ALM inclusion for one of them. Quantitative results analysis from formal assessment questions and overall performance of both groups are presented and discussed. Student's opinions regarding the ALM are also presented.

INTRODUCTION

Statics is a course that lays the foundational concepts and is present in almost every engineering major. Additionally, it is pre-requisite for other courses such as dynamics, mechanics of materials and solid mechanics and it is in the critical path to graduation. Moreover, the failing (WDF)/ pass (ABC) ratio for statics is very high (40%- 50%) causing many students to abandon engineering to pursue other majors. At the University of Central Florida, students are not officially declared as part of their engineering majors until they approve and master this important class.

Bad teaching strategies and lack of identification with the major are also reasons for students withdrawing from engineering programs, especially during the first years. Education research has shown an increase in class success, retention, and graduation rates when the students participate in relevant learning experiences[1-7]. A growing number of research publications in engineering education support the necessity to complement purely traditional lecture-based learning environment with practical class applications and demonstrations to adequately prepare students to succeed in the collaborative and challenging engineering career. The use of strategies such as studying physical models, manipulatives, multidisciplinary teamwork, and experiential learning has been documented to enhance spatial visualization and to help in closing engineering students' gap between theory, previous knowledge, and real life situations [8-16]. Other aspect identified linked with the success of engineering students is their physics and mathematics background [17]. The authors stated that the mathematical knowledge gained prior and during engineering education is highly essential in engineering practice. Another study shown in [18] revealed that mathematics performance significantly influences on the student academic performance in chemical and process engineering programs. In [19] a research was conducted with the goal of investigating what are the most needed mathematical pre-requisite knowledge for a Statics and Dynamics course.

The purpose of this research was to investigate the impact of incorporating an Adaptive Learning Module (ALM) in Statics, to review the mathematical prerequisite knowledge needed by the Statics' students.

METHODOLOGY

Research Questions
This study focused on answering two research questions:

1) Do students perform better in Statics after the inclusion of ALM for reviewing the required mathematical previous knowledge?
2) How the inclusion of an ALM affects the different students' sub-groups such as gender and ethnicity?

Research Design and Control
To answer these questions, two Statics sections were taught in the same manner by the same instructor, the only difference was the inclusion of ALM in one of them.

Description of the Adaptive Learning Module (ALM): The first step was to identify the Mathematical Background Knowledge (MBK) needed for Statics. Sometimes students may have passed the pre-requisite courses and still they fail to relate what they learned with the application of those concepts. By deconstructing typical Statics questions for every Statics class-learning goal, the authors prepared a set with the bare minimum needed skills: Basic algebra, scientific notation, Pythagorean theorem, finding roots of equations, linear, quadratic, and cubic functions, vectors, area under curves, trigonometry, and systems of linear equations.

A mastery-based learning platform called ALEKS (Assessment and Learning Knowledge Spaces) was used as a review module for the MBK. ALEKS (McGrawHill) is an adaptive learning program designed to help learning math. By using artificial intelligence, this ALM determines each student initial knowledge and starts from there, creating an individualized learning plan that guides them throughout their review process, assessing their performance as well.

The additional homework was divided in three parts each one due before the previous knowledge was needed in Statics.

Part 1 consisted of 29 topics related to trigonometric equations and vectors. The average of students'mastering for these topics was 24.30. Part 2 contained 23 topics related to lines and systems of linear equations of which 21.6 were mastered by students, and Part 3 reviewed 18 topics of inequalities, geometry, and quadratic functions (students mastered 17.5 in average) See Figure 1.

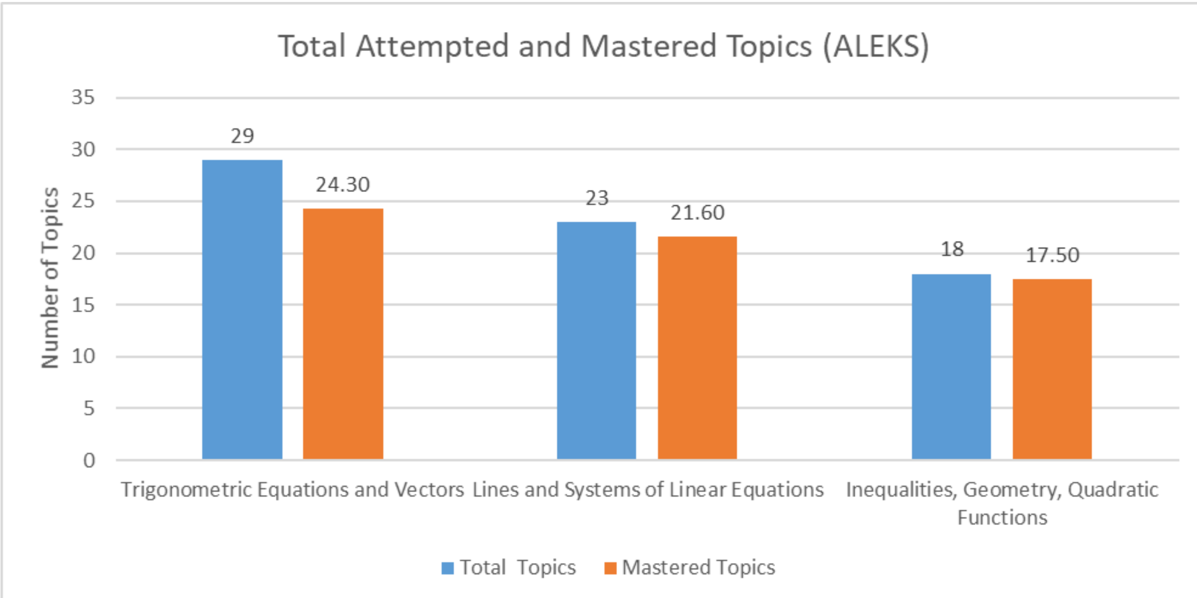

Figure 1. Total Attempted and Masterd Topics (ALEKS)

The students spent an average amount of 8 hours and 45 min completing all the three parts with a minimum time of 53 min and a maximum of 16 hours and 51 min with a standard deviation of 3 hours and 57 min. Figure 2 shows the histogram of time invested by the students in ALEKS.

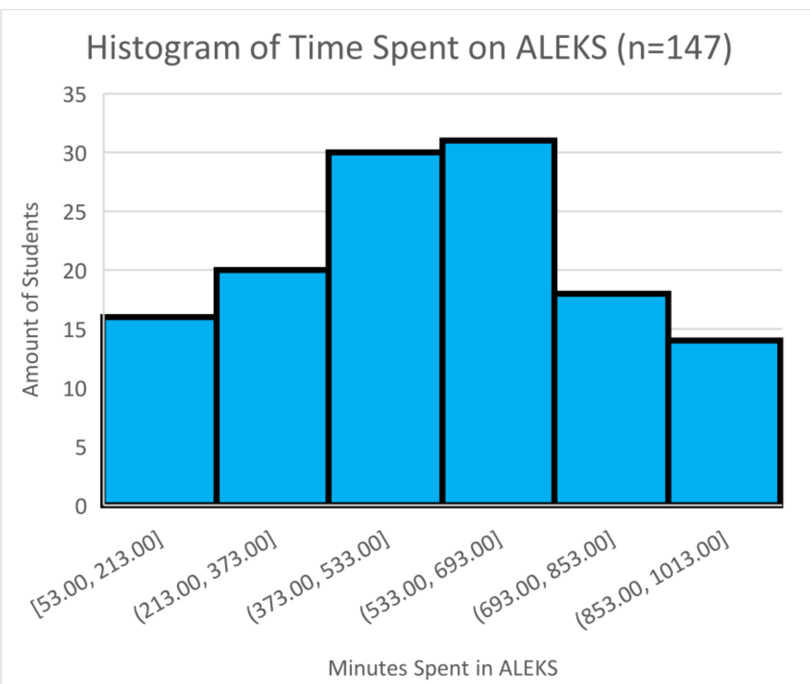

Figure 2. Histogram of time spent by the students in ALEKS

Figure 3 shows the time spent by day in ALEKS with the three peaks coinciding with the deadline of each one of the three parts of the additional homework.

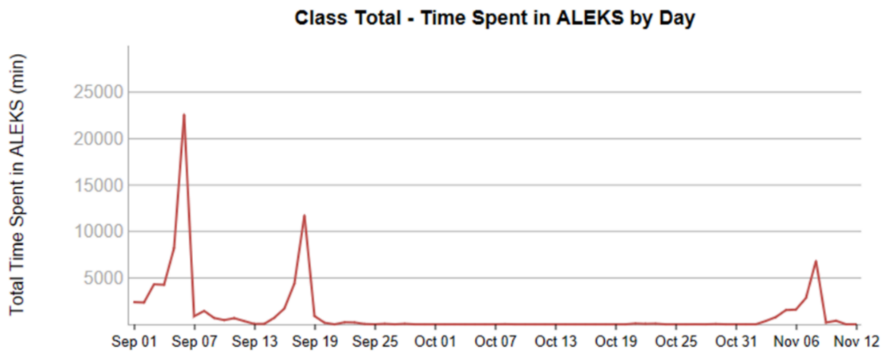

Figure 3. Total Time Spent in ALEKS by Day

PARTICIPANTS

Rigorous analysis was performed on the participant data to ensure the validity of the study.

Instructor
The same instructor was in charge of delivering of the material and assessment for both studied sections. Both courses were mixed mode: instructional material was made available to de students in the form of videos and study sets. The assessment consisted of on-line homework, hands-on homework, and proctored computer-based assessments. The only difference was the inclusion of one additional homework (the ALM) for one of the sections (Identified as Section 5 herein)

Students
Students enrolled in the course in accordance with their schedules and time preference. Data from both sections were analyzed to determine if both groups were similar of differed in any way. These analyses used data housed by Institutional Knowledge Management (IKM) of the University, which includes student's demographics such as gender, classification (sophomore, junior, senior), ethnicity, enrollment, and cumulative GPA.

Analysis Methods
The research compares the performance of the students (pass/fail) in either sections using descriptive analyses employing one variable and two variable relationships. The relationships considered include: (a) for one variable: comparing the grade distribution across the sections with and without ALM, gender, ethnicity, student level, and prior GPA (b) for two variables: grade performance by gender and ALM, and ethnicity and ALM. Further, we build on the descriptive analyses by developing individual level models of student grade performance while controlling for several covariates simultaneously. The modeling approach controls for several student characteristics and is more likely to offer stable model attribute impacts on grade compared to descriptive analysis where the analyst has no control over variables not included in the analysis.

DATASET DESCRIPTION

Final dataset consists of all records of the statics students in Fall semester in 2019. The estimation set consists of 253 observations. The Grade outcome variable was considered in two forms: a) binary outcome variable (Pass/Fail) and b) five level grade outcome variable (a-f).The independent variables consist of different demographic characteristics of the students such as gender, race, students' classification by level of study, overall GPA prior to the course, and number of prior attempts. Descriptive statistics of the final dataset are provided in Table 1

Summary Tables for the Participants

Variables	Description	Frequency	Percent
Gender			
0	Female	52	20.6
1	Male	201	79.4
Race			
1	White	122	48.2
2	Asian	14	5.5
3	AA	17	6.7
4	Hispanic	74	29.2
5	Others	26	10.3
Level			
1	Junior	138	54.5
2	Senior	57	22.5
3	Sophomore	52	20.6
4	Others	6	2.4
UCF GPA			
1	4.00-3.50	45	17.8
2	3.50-3.00	64	25.3
3	3.00-2.50	39	15.4
4	2.50-0.00	30	11.9
5	Unavailable	75	29.6
Overall GPA			
1	4.00-3.50	68	26.9
2	3.50-3.00	99	39.1
3	3.00-2.50	60	23.7
4	2.50-0.00	26	10.3
Prior Attempts			
0		218	86.2
1		28	11.1
2+		7	2.8
Adaptive Learning Method			
0	No	107	42.3
1	Yes	146	57.7

Official Grade			
2	Pass	171	67.6
1	Fail/Withdraw	82	32.4

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Univariate Analysis

In an univariate analysis of the variables, one to one comparisons between selected exogenous variables and the target variable (grade) are performed to investigate potential associations between them. The comparisons tried to identify the possible significant distributional difference of grade across subgroups using chi-square statistics. Cross-tabulations between exogenous variables versus grade are presented in tables (2-7) below:

Table 2 Gender Vs Grade:

		Gender		Total
		Female	Male	
Grade	F/W	17	65	82
	Pass	35	136	171
Total		52	201	253

* Chi-square statistics = 0.002 (df = 1, p-value = 0.961)

Table 3 Race Vs. Grade:

		Race					Total
		White American	Asian	African American	Hispanic	Others	
Grade	F/W	35	5	10	19	13	82
	Pass	87	9	7	55	13	171
Total		122	14	17	74	26	253

* Chi-square statistics = 11.460 (df = 4, p-value = 0.022)

Table 4 Level Vs. Grade:

		Level				Total
		Junior	Senior	Sophomore	Others	
Grade	F/W	49	25	7	1	82
	Pass	89	32	45	5	171
Total		138	57	52	6	253

* Chi-square statistics = 13.217 (df = 3, p-value = 0.004)

Table 5 Overall GPA Vs. Grade:

		Overall GPA				Total
		3.50-4.00	3.00-3.50	2.50-3.00	<2.50	
Grade	F/W	6	30	31	15	82
	Pass	62	69	29	11	171
Total		68	99	60	26	253

* Chi-square statistics = 35.213 (df = 3, p-value = 0.000)

Table 6 Prior Attempts Vs. Grade:

		Prior Attempts			Total
		0	1	2+	
Grade	F/W	70	8	4	82

	Pass	148	20	3	171
Total		218	28	7	253

* Chi-square statistics = 2.152 (df = 2, p-value = 0.341)

Table 7 Adaptive Learning Vs. Grade:

		ALM		Total
		No	Yes	
Grade	F/W	41	41	82
	Pass	66	105	171
Total		107	146	253

* Chi-square statistics = 2.953 (df = 1, p-value = 0.086)

From the above univariate analysis, it is found that race, level and overall GPA prior to the course are potentially important variables for predicting future grade of the students in statics course. On the other hand, chi-square statistics also shows that gender, number of prior attempts and inclusion of adaptive learning module do not significantly influence the grade.

MODEL AND ESTIMATION RESULTS

Econometric Model

In this research, we employ the ordered logit model for studying the ordinal categorical variable grade with the categories defined as Fail/Withdraw (DFW) and Pass (ABC).

Let *j* be the index for the discrete outcome that corresponds to grade for student q. In ordered response model, the discrete grade levels (y_q) are assumed to be associated with an underlying continuous latent variable (y_q^*). This latent variable is typically specified as the following linear equation:

$$y_q^* = \alpha' z_q + \varepsilon_q,\ y_q = j \text{ if } \psi_j < y_q^* < \psi_{j+1} \qquad (1)$$

where, z_q is a column vector of exogenous variables for student q, α is column vector of unknown parameters, ψ_j is the observed lower bound threshold and ψ_{j+1} is the observed upper bound threshold for grade j. ε_q, with logistic distribution, captures the idiosyncratic effect of all omitted variables for student q.

$$Pr(y_q = j) = \Lambda\left(\psi_{j+1} - \alpha' z_q\right) - \Lambda\left(\psi_j - \alpha' z_q\right) \qquad (2)$$

where, $\Lambda(.)$ is the cumulative standard logistic distribution.

The likelihood function with the probability expression in equation (2) for grade outcome can be expressed as:

$$L = \prod_{q=1}^{Q} \left[\prod_{j=1}^{J} \left\{ Pr(y_q = j) \right\}^{\omega_{qj}} \right] \qquad (3)$$

where, ω_{qj} is dummy with $\omega_{qj} = 1$ if the student q sustains a grade of j and 0 otherwise. All the parameters in the model are then consistently estimated by maximizing the logarithmic function of L.

RESULTS SUMMARY

Binary Outcome Model

Error! Reference source not found. shows parameter estimates of the ordered logit model where effects of adaptive learning method and other factors on final grade of the students can be captured. Positive (negative) coefficient corresponding to a parameter indicates that value of the parameter being one actually increases (decreases) the probability of higher grade.

Table 8 Parameter Estimates of Binary Logit Model

Variables	**Estimates**	**t-statistics**
Threshold		
Threshold (Fail-Pass)	0.6069	2.029
Propensity Component		
Level (Base: Other Levels)		
Sophomore	1.0663	2.282
Overall GPA (Base: 0.00-3.00)		
3.50-4.00	2.6109	5.209
3.00-3.50	0.8750	2.693
Prior Attempts (Base: 0 and 2+)		
1	0.7832	1.625
Adaptive Learning Module (Base: No)		
Yes	0.7116	2.141
Interaction of Race with ALM (Base: White American And Hispanic)		
Race Others * ALM	-1.1403	-2.431
Model Fitness		
Number of observations	253	
Initial Log-likelihood	-175.366	
Log-likelihood at convergence	-131.574	
ρ^2	0.250	
Adjusted ρ^2	0.210	

Students' Level
Level of the student is an important determinant of grade. In general, sophomore students have higher chance to pass than junior, senior and other students. It may indicate the fact that junior and senior students fail more in their first (or second) enrollment and, this time they are retaking the course. Similar to their previous attempts, they performed poor this time as well.

Overall GPA

Intuitively, overall GPA of a student prior to the course is an important factor of his/her future grade. Parameter estimates show that students having GPA 3.00-4.00 actually perform better compared to the students having GPA below 3.00 .

Prior Attempts

Students, taking referencesstatics course as their second enrollment, have higher probability of passing compared to the fresher students and the students, who were enrolled in the course twice (or more) before.

Main Effect of Adaptive Learning

Parameter estimates shows that effect of ALM on grade is statistically significant. A student from a class with ALM performs better in terms of passing than student from a class without ALM in general.

Interaction of Race of the students with ALM

Race of a student is found to influence the effect of adaptive learning method on the grade of statics course. Parameter estimates show that effect of adaptive learning module is moderated if the student belongs to other groups instead of White American and Hispanic. This means that adaptive learning module has a positive effect for White American and Hispanic students but very negligible effect is shown for students from other groups. This could be mainly explained because of the size of the samples being too small for this study.

Five Level Grade Outcome Model

In our study, we also performed the analysis using 5 level response variable for grade (A-F). The parameter estimates in Table 9 are reasonably similar to the specifications for the two level classification of grade. One major difference is the slightly marginal significance of ALM main effect. However, it is important to recognize that ALM interaction with Race has a significant impact. Parameter estimates for ordered logit model are provided in the Table below:

Table 9 Parameter Estimates of Ordered Logit Model

Variables	**Estimates**	**t-statistics**
Threshold		
Threshold F-D	-0.0116	-0.047
Threshold D-C	0.3559	1.437
Threshold C-B	1.4436	5.403
Threshold B-A	3.2657	10.048
Propensity Component		
Level (Base: Other Levels)		
Sophomore	0.6523	2.182
Overall GPA (Base: 0.00-3.00)		

3.50-4.00	2.7364	7.805
3.00-3.50	0.8072	2.954
Prior Attempts (Base: 0 and 2+)		
1	0.8396	2.232
Adaptive Learning Module (Base: No)		
Yes	0.2427	0.973[1]
Interaction of Race with ALM (Base: White American And Hispanic)		
Race Others * ALM	-0.616	-1.674
Model Fitness		
Number of observations	253	
Initial Log-likelihood	-407.188	
Log-likelihood at convergence	-342.549	
ρ^2	0.159	
Adjusted ρ^2	0.134	

[1]= parameter is insignificant at 90% confidence limit

STUDENTS PERCEPTION RESULTS (SURVEY)

ALM students were asked to complete an anonymous Qualtrics survey and the results are shown in Figure 4. Out of 147 students in the class, 108 participated in the poll. In Figure 4a) 60.19% of the students strongly agreed and agreed with the question if reviewing vectors with ALKES improved their performance in Statics vs. 21.30% that disagreed or strongly disagreed. Regarding if ALEKS review on systems of equations helped them to perform better in the class (Figure 4b), 44.44% agreed vs. 36.11% disagreed. 61.11% expressed their agreement with the ALM be effective for reviewing trigonometry and geometry needed for Statics as shown in Figure 4c. Answers to the question if the ALM was beneficial for improving their performance in the class are summarized in Figure 4d. 69.44% agreed or strongly agreed and only 13.89 disagreed.

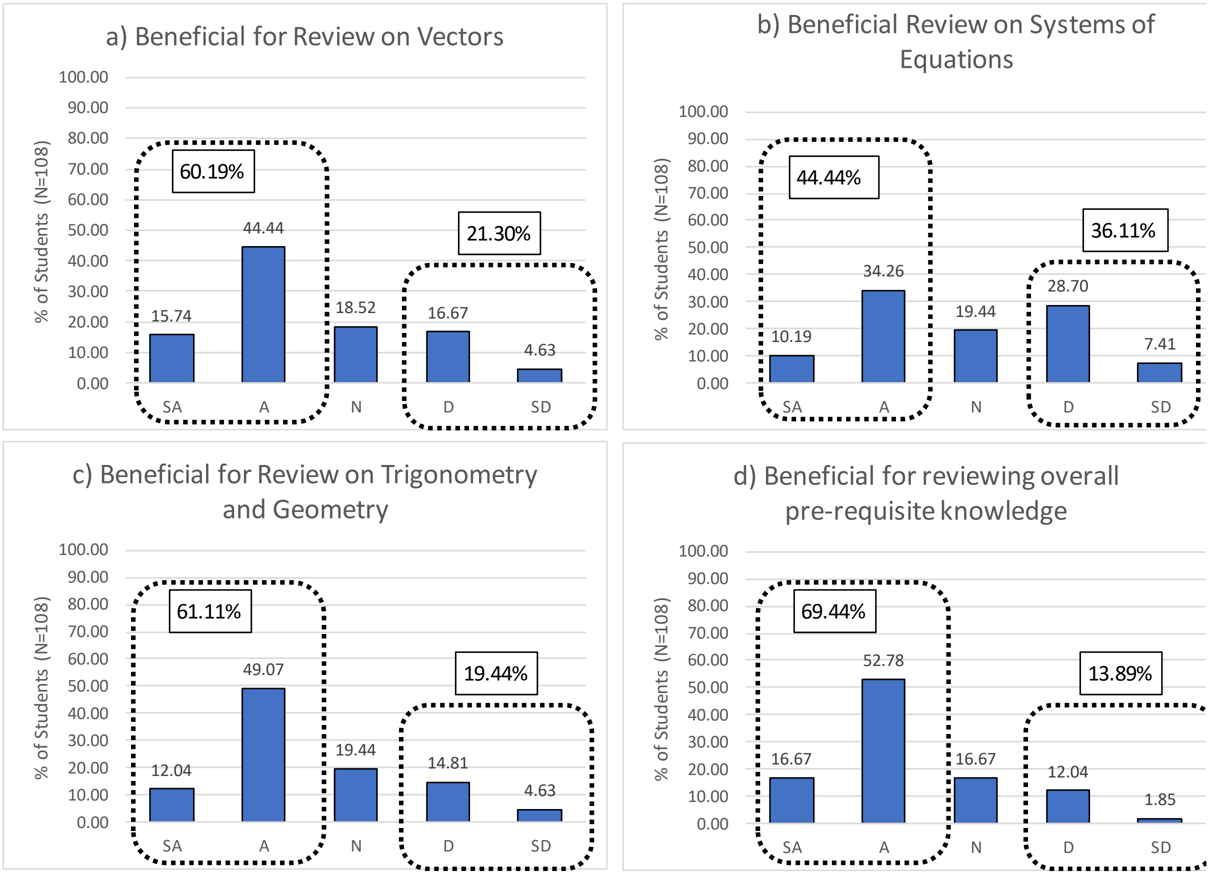

Figure 4. Responses from Surveys Applied to ALM Students

FINDINGS, CONCLUSIONS, LIMITATIONS, AND FUTURE WORK

This research investigated the effect of introducing an ALM (ALEKS) into a large-size engineering class called Engineering Analysis-Statics. Statics was selected for several reasons such as being in the graduation critical path as a required common prerequisite and corequisite for more advanced engineering courses, having a large enrollment (around 1,700 per year), and presenting a high fail pass ratio of about 40-50%. Two main aspects were studied: students' success in the class and students' results per gender and ethnicity.

Two multivariate models were estimated: (a) pass/fail outcome and (b) grade outcome (classified in 5 levels) using a multivariate ordered logit model. In these models, the effects of adaptive learning method and other factors on the final grade of the students was captured. The model results offer several important findings. First, the pass/fail model clearly highlights the role of ALM in increasing pass rate while controlling for a host of other student attributes. Second, in the Grade prediction model with five levels, the impact of ALM was positive and yet insignificant. This is an interesting finding that warrants further analysis with larger datasets. Finally, it was also found that in several student attributes affect grade outcome. Sophomore students have higher chance to pass than junior, senior and other students. Students, taking statics course as their second enrollment, have higher probability of passing compared to the fresher students and the students, who were enrolled in the course twice (or more) before. Parameter estimates show that students having GPA 3.00-4.00 actually perform better compared to the students having GPA below 3.00 and unknown GPA. Regarding the students' success per ethnicity and gender, the study also showed that Race of a student is found to influence the effect of adaptive learning method on the grade of statics course. Parameter estimates show that effect of adaptive learning module is moderated if the student belongs to other groups instead of White American and Hispanic. This means that adaptive learning module has a positive effect for White American and Hispanic students but very negligible effect is shown for students from other groups (very small sample sizes).

This analysis was limited for the small size of some samples for example African American women or African American men however, this is an ongoing study. More data is being collected and soon will be ready for analysis.

In addition to the model results generated, the students' perception is that ALEKS helped them to better perform in the class by reviewing the math pre-requisite knowledge.

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