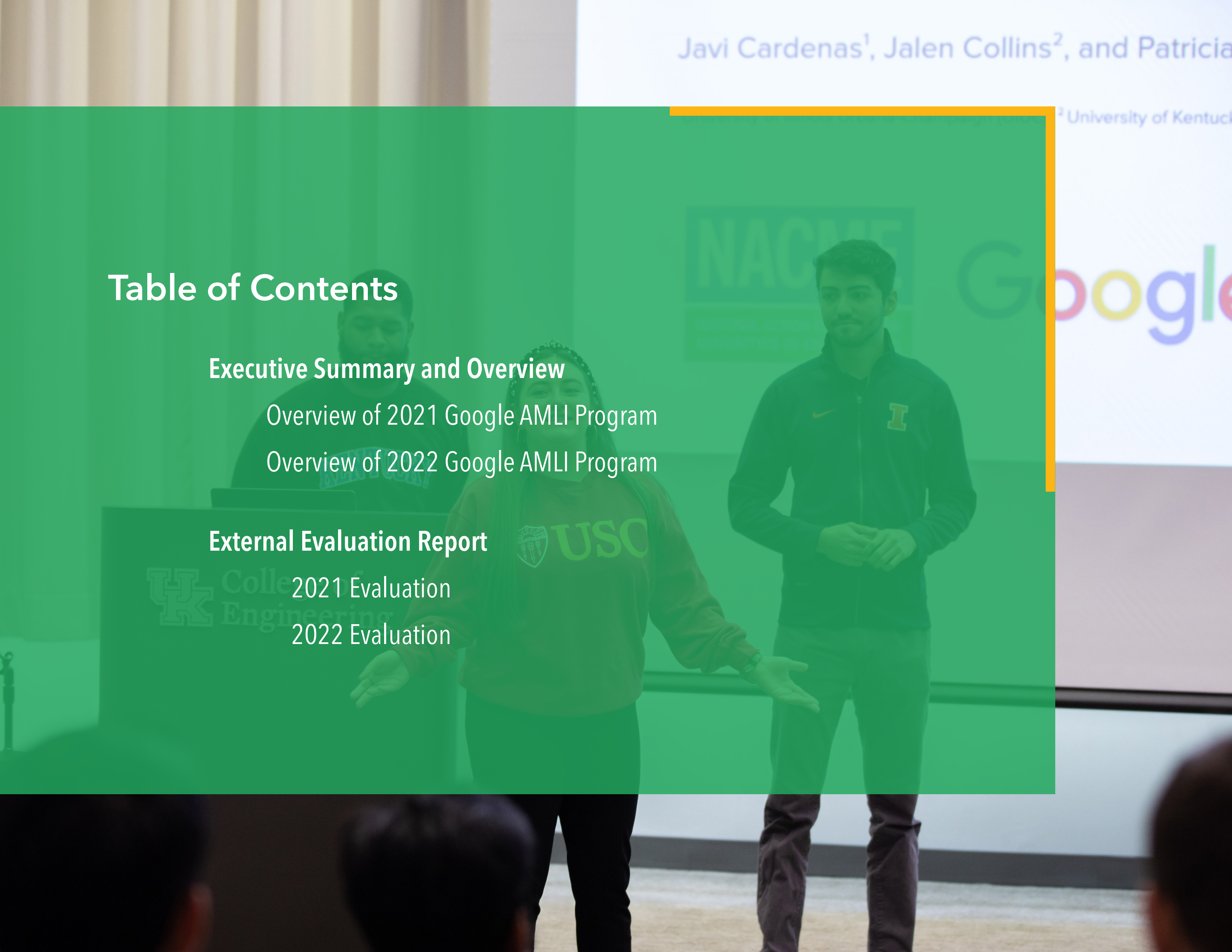
NACME

NATIONAL ACTION COUNCIL FOR MINORITIES IN ENGINEERING

Evaluation Report: NACME AMLI Boot Camp supported by Google.org



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2021 - 2022

C.A.S.E. Academy

Introduction and Executive Summary

As technological innovation and advancement continues to impact all industries and sectors of the economy, influencing every aspect of our lives including how we work, learn, and communicate, computational literacy is critical for all students. Despite the increased significance of computer science education, computational thinking, and computing literacy across all fields and occupations, access to computer science education is unequally distributed by race, gender, socioeconomic status, and geography. Google AMLI Bootcamp was designed in collaboration with NACME and Google education to address this issue. Sponsored by the National Action Council for Minorities in Engineering (NACME) and Google Education, an eight-week program exposed under-represented minority (URM) undergraduate students to advanced concepts in artificial intelligence and machine learning (ML) using Google Education's open-sourced curriculum. Participating students receive full room and board for the duration of the program, a travel stipend to cover arrival and departure costs and upper-level computer science elective course credit for completing the bootcamp. Instructors dedicated classroom time to hands-on learning featuring faculty-supported, collaborative project work. Students were also granted access to a professional development webinar series where they were introduced to inspiring technology professionals sharing critical aspects for launching and sustaining a successful career.

For two consecutive summers, 2021 and 2022, NACME coordinated the Google AMLI Bootcamp. Three innovative models for course delivery were utilized:

1. University of Kentucky – in person instructions both summers
2. University of Arkansas – partial in person instruction both summers
3. Morgan State University – completely online in 2021 and partial in person instruction for 2022

To support the long-term development of the project NACME commissioned an evaluation study. The evaluation plan was designed to provide feedback on progress toward meeting the learning objectives outlined in the curriculum as well as formative aspects to guide evidence-based based decisions about changes in activities through daily feedback from students on assessment of learning of the content. Students also provided weekly feedback on the program activities and the professional development series. Input was also collected from faculty/instructors and teaching assistants on their experience with delivering the content and helping students acquire knowledge to support their overall learning. This comprehensive report includes a description of the instruments/metrics for the project and disaggregated data by performance site on a weekly basis. Participant data is also disaggregated data by race, ethnicity, gender, academic

Summary of Finding from Year 1 (2021)

A pre-survey was administered to students enrolled in the Applied Machine Learning course during the first week of the course. A total of 59 students responded across the three institutions. The typical student identified as male (62.7%), African American (55.9%), non-Hispanic (54.2%) and without a disclosed disability (93.2%). Nearly 60% of the students were of junior or senior status and 55.9% reported majoring in Engineering and approximately 60% expected to earn at least a Masters' degree. Sample characteristics were not requested on the post survey.

A longitudinal design (pre-post) was also used to examine changes (improvements) for course participants (students, faculty and teaching assistants) over the eight-week course. Throughout the eight-week courses, students were provided the opportunity to provide daily and weekly feedback and a sample of students participated in a focus group. A total of 61 students were participated in the course from three different sites (Arkansas, n=21, Kentucky, n=17, Morgan State, n=23). Faculty offered instruction from Arkansas and Kentucky on alternative days with teaching assistants provided at all three sites.

Students expected this Applied Machine Learning course to be valuable with 85% indicating that they expected the course to be helpful in getting an internship and 81% believing it would be helpful in getting a job. In addition, 69% indicated that they wanted to learn more about machine learning and they would learn something useful for their other classes. While faculty and TAs also believed that this course would be helpful in getting internships and jobs, they most strongly believed students enrolled because they liked the applications of machine learning.

Daily and weekly feedback provided over the first 7 weeks of the course was positive. Daily feedback was generally most positive in relation to the instructor's command of the content and the helpfulness of the teaching assistants (TAs) with responses consistently averaging above 4.0 (using a 5-pount scale). Weekly feedback was also supportive with overall average responses above 4.0 for 5 of the 7 weeks. Students responded most favorably in weeks 1 and 7 and least favorably toward the midway points in weeks 4 and 5 when students expressed some difficulty keeping up with the pace and understanding what was addressed in class. A focus group with students after week 3 also revealed participating virtually created technical and learning challenges and these students preferred to have an instructor in the room with them and that was often reflected in the numerical responses to the daily and weekly feedback.

Post course responses were very positive with all averaging above 3.75 and 11 of the 15 above 4.0. Students reported great improvement in their confidence to complete their degree (M=4.2) and earn an advanced degree or get a job after graduation (M=4.3). They also reported great improvement in their communication skills (M=4.23), problem-solving ability (M=4.26) and ability to work effectively with others (M=4.28). Overall, students planned to keep in touch with other students from the course (M=4.51) and valued the residential component (M=4.43). They also established strong relationships with faculty and planned to keep in touch (M=4.23) and believed they were better prepared for the coming year (M=4.28). Finally, getting a stipend was important to them (M=4.41).

Faculty reported high levels and improved levels of confidence in their ability to teach Engineering concepts, use instructional and assessment strategies, motivate students to learn and engage students in the learning process. TAs were especially confident that they helped students with their teamwork, technology, communication and critical thinking skills and reported improved confidence in their ability to create a positive learning environment, use instructional strategies and perform their essential TA duties. In addition , TAs became more confident in their ability to help students give and receive feedback, prepare presentations and deliver strong oral presentations and were especially confident that they helped students with their teamwork, technology, communication and critical thinking skills.

Students indicated moderate to high levels of confidence in their knowledge and abilities related to the Applied Machine Learning Course student learning outcomes and in the specific topics addressed in the course with all post-course responses exceeding those prior to the course. At the end of the course, students also reported greater engineering self-efficacy (general and skill-related), confidence in their 21st century skills (e.g. working with peers and persons with different backgrounds), intention to persist and readiness for a career. A matched sample of 59 students was examined to determine the extent to which students changed (improved) from the beginning of the course to the end and resulted in improvements for 14 of the 16 examined scales. After controlling for Type 1 error, statistical significance was found in relation to student confidence in their knowledge and skills required for the machine learning topics addressed in the course and the expected student learning outcomes at each site. Follow-up analysis revealed statistically significant improvement for all six SLOs and 34 of the 39 topics. Students participating at Kentucky also reported statistically significant increases in their confidence and ability related to the ABET SLOs, engineering efficacy and peer learning.

Summary of Finding from Year 2 (2022)

A longitudinal design (pre-post) was also used to examine changes (improvements) for students while faculty and TAs were only requested to provide feedback at the end of the course. Throughout the eight-week courses, students were provided the opportunity to provide weekly feedback and a sample of students participated in a focus group. In 2022 A total of 62 students were participated in the course from three different sites (Arkansas, n=21, Kentucky, n=17, Morgan State, n=24). The typical student identified as male (74.6%), African American (74.6%), non-Hispanic (73%) and without a disclosed disability (90.5%). Overall, nearly 60% of the students were of junior or senior status and 55.6% reported majoring in Engineering and over 40% expected to earn at least a Masters' degree. In 2021

Faculty offered instruction from Arkansas and Kentucky on alternative days with teaching assistants provided at all three sites.

Students expected this Applied Machine Learning course to be valuable for a variety of reasons. In the overall sample, over 50% indicated that they thought they would learn something useful for their classes (60%), were curious to know more about machine learning (60%), just wanted to learn something new (60%), thought the course would be helpful in getting an internship (61%) and getting a job (66%).

Weekly feedback was summarized from the first 6 weeks in relation to the quality of instruction and professional development (PD) sessions. Students responded each week and indicated was of high quality with overall average responses of 4 or above in weeks 1 to 5 and just slightly lover (3.93) in week 6. While students believed that instructors demonstrated command of content knowledge and that they were learning things useful for their other classes and their careers, they did have a more difficult tome keep up with the pace and indicated that they did not have as good an understanding of the materials as the weeks progressed. Students found the PD sessions to be of great interest, they helped them think of additional PD opportunities, helped prepare for potential internships and motivated them to improve their preparation for a career in Engineering.

Post course feedback was very positive with over 90% of students indicating that they gained valuable knowledge and learned useful applications related to machine learning and valued the networking with other students. Students also strongly agreed that they established strong relationships with faculty and will keep in touch (M=4.31), planned to keep in touch with students they met (M=4.34) and are better prepared for the coming year after completing this course (M=4.34). Furthermore, students' retrospective pre-post feedback was very positive with an overall average of 4.08 (using a 5-point scale). Students expressed the most improvement in their confidence that they will get a job earn and advanced degree upon graduation (M=4.40) and their awareness of potential careers in machine learning (M=4.31).

Post course feedback also provided support for culturally responsive teaching with an overall scale average of 3.93 (using a 5-point scale) and all 27 items averaging above 3.5. Students most strongly agreed that their instructors explained new concepts using examples taken from students' everyday lives (M=4.15), built a sense of trust in students (M=4.16) and developed personal relationships with students (M=4.23). Students strongly believed that culturally responsive teaching would be expected to result in positive outcomes with an overall scale average response of 4.45 (using a 5-point scale). More specifically, students strongly agreed that when students see themselves in the pictures and examples used in class, they develop a positive self-identity (M=4.52), using a variety of instructional approaches helps students be successful (M=4.54), students are more motivated and engaged when a personal relationship is established between the instructor and student (M=4.55) and students will be successful when instruction is adapted to meet their needs (M=4.57).

Finally, a matched sample of students was examined to determine the extent to which students changed (improved) from the pre course to post course survey administrations. Students reported improvement each of the 11 scales examined with 9of these 11 comparisons reaching the minimum criteria for statistical significance ($< .05$). More specifically, students significantly improved their confidence in meeting each of the 6 ML course student learning outcomes and their confidence related to 38 of the 39 course topics/units. In addition, students also reported significant higher engineering efficacy, confidence in meeting the ABET SLOs and persistence at the end of the course.
As a result of participating in the Google AMLI bootcamp students at all sites showed significant gains in their knowledge of machine learning concepts. The analysis of results, in Tables 1-3, from the 2022 Google AMLI bootcamp show students reported significant gains in their knowledge of the machine learning student learning objectives (SLOs) at each site. While the detailed weekly analysis of feedback from students by site showed some variation in level of confidence in grasping the concepts, over time each site showed significant increases in students knowledge of machine learning concepts. Therefore each model can serve as an effective model for increasing machine learning content knowledge for students from historically underrepresented groups.

Conclusion

As a result of participating in the Google AMLI bootcamp students at all sites showed significant gains in their knowledge of machine learning concepts. The analysis of results, in Tables 1-3, from the 2022 Google AMLI bootcamp show students reported significant gains in their knowledge of the machine learning student learning objectives (SLOs) at each site. While the detailed weekly analysis of feedback from students by site showed some variation in level of confidence in grasping the concepts, over time each site showed significant increases in students knowledge of machine learning concepts. Therefore each model can serve as an effective model for increasing machine learning content knowledge for students from historically underrepresented groups.

Changes over time by Site the 2022 Google AMLI

Changes over the duration of the course were also examined for each site. These findings are summarized in the following tables. -Over the duration of the course, students from the University of Arkansas reported improvement for 10 of the 11 scales summarized below with statistically significant improvement related to the course SLOs, ABET SLOs and confidence in the course content topic areas.

University of Arkansas		Pre Couse	Post Course		
Scale	N	Mean (SD)	Mean (SD)	t (p)	Effect Size (Cohen's d)[a]
ML Course SLOs	20	2.41 (1.12)	4.16 (.76)	7.29***	1.63
ABET SLOs	20	3.86 (.87)	4.32 (.68)	2.36*	.527
MK Course Unit Confidence	20	2.33 (.85)	3.87 (.66)	11.12***	2.49
Engineering Efficacy - Total	20	4.12 (.56)	4.33 (.66)	1.53	.343
General	20	4.30 (.55)	4.53 (.67)	1.28	.286
Skills	20	4.21 (.63)	4.47 (.59)	1.62	.363
Design	20	4.03 (.67)	4.22 (.78)	1.16	.260
Tinkering	20	3.98 (.71)	4.15 (.77)	1.17	.262
Persistence	20	4.01 (.64)	4.31 (.73)	1.59	.356
Career Development Units	19	4.01 (.66)	3.98 (.88)	-.196	-.045
Career Readiness	20	4.11 (.71)	4.18 (.69)	.384	.086
*p<.05, **p<.01, ***p<.001 a-.2=small, .5=medium, .8=large					

Table 1 University of Arkansas Comparison of Pre and Post Results for 2022 Google Bootcamp

Changes over time by Site the 2022 Google AMLI

Over the duration of the course, students from the University of Kentucky reported improvement for each of the 11scales summarized below with statistically for significant improvement related to the course SLOs, ABET SLOs, confidence in the course content topic areas, engineering efficacy and career readiness.

University of Kentucky		Pre Couse	Post Course		
Scale	N	Mean (SD)	Mean (SD)	t (p)	Effect Size (Cohen's d)[a]
ML Course SLOs	17	2.31 (.89)	4.25 (.63)	7.51***	1.82
ABET SLOs	17	3.56 (.89)	4.34 (.59)	3.69**	.923
MK Course Unit Confidence	17	2.24 (.73)	3.99 (.62)	8.89***	2.16
Engineering Efficacy - Total	17	3.85 (.52)	4.46 (.62)	3.86**	.937
General	17	4.23 (.58)	4.61 (.55)	2.74*	.664
Skills	17	4.10 (.60)	4.64 (.48)	3.99**	.967
Design	17	3.85 (.77)	4.48 (.77)	3.79**	.921
Tinkering	17	3.42 (.99)	4.22 (1.11)	3.68**	.892
Persistence	17	4.00 (.56)	4.28 (.60)	1.78	.432
Career Development Units	16	3.67 (.95)	4.04 (.86)	1.93	.468
Career Readiness	17	3.84 (.79)	4.31 (.67)	3.13**	.760
***p<.05, **p<.01, ***p<.001** **a-.2=small, .5=medium, .8=large**					

Table 2 University of Kentucky Comparison of Pre and Post Results for 2022 Google AMLI Bootcamp

Changes over time by Site the 2022 Google AMLI

Over the duration of the course, students from the Morgan State University reported improvement for 8 of the 11scales summarized below with statistically for significant improvement related to the course SLOs, confidence in the course content topic areas, and general and design engineering efficacy

Morgan State University		Pre Couse	Post Course		
Scale	N	Mean (SD)	Mean (SD)	t (p)	Effect Size (Cohen's d)[a]
ML Course SLOs	22	1.96 (.76)	3.79 (.57)	10.18***	2.17
ABET SLOs	22	3.61 (.76)	3.94 (.57)	1.92	.409
MK Course Unit Confidence	22	1.97 (.59)	3.23 (.75)	6.58***	1.40
Engineering Efficacy – Total	22	3.99 (.72)	4.19 (.49)	2.07	.441
General	22	4.12 (.68)	4.35 (.58)	2.17*	.462
Skills	22	4.10 (.73)	4.21 (.59)	1.03	.220
Design	22	3.77 (.89)	4.14 (.58)	2.49*	.533
Tinkering	22	3.94 (.97)	4.05 (.59)	.683	.146
Persistence	22	4.04 (.53)	4.01 (.62)	-.169	-.036
Career Development Units	22	4.01 (.67)	3.97 (.73)	-.352	-.075
Career Readiness	22	4.24 (.55)	4.19 (.59)	-.451	-.098
*p<.05, **p<.01, ***p<.001 a-.2=small, .5=medium, .8=large					

Table 3 Morgan State University Comparison of Pre and Post Results for 2022 Google AMLI Bootcamp

Applied Machine Learning Course Evaluation

JUNE 7 – JULY 30

EVALUATION REPORT –2021

David M. Shannon, Auburn University

C.A.S.E. Academy

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Appendices

Participants

Students - A pre-survey was administered to students enrolled in the Applied Machine Learning course during the first week of the course. A total of 59 students responded across the three institutions. The typical student identified as male (62.7%), African American (55.9%), non-Hispanic (54.2%) and without a disclosed disability (93.2%). Nearly 60% of the students were of junior or senior status and 55.9% reported majoring in Engineering and approximately 60% expected to earn at least a Masters' degree. Sample characteristics were not requested on the post survey.

Sample Characteristics	Overall Sample (N=59)	Arkansas (n=20)	Kentucky (n=16)	Morgan State (n=23)
Gender (Pronoun)				
He	37 (62.7%)	12 (60%)	10 (62.5%)	15 (65.2%)
She	22 (37.3%)	8 (40%)	6 (37.5%)	8 (34.8%)
Prefer not to answer				
Hispanic				
No	32 (54.2%)	5 (25%)	6 (37.5%)	21 (91.3%)
Yes	22 (37.3%)	13 (65%)	9 (56.3%)	0
Prefer not to answer/no response	5 (8.5%)	2 (10%)	1 (8.3%)	2 (8.7%)
Race[a]				
Am. Indian/Alaskan Native	1 (1.7%)	1 (5%)	0	0
Asian or Pacific Islander	6 (10.2%)	3 (15%)	1 (6.3%)	2 (8.7%)
Black or African American	33 (55.9%)	3 (15%)	8 (50%)	22 (95.7%)
Native Hawaiian or Pacific Islander	1 (1.7%)	0	0	1 (4.3%)
White	14 (23.7%)	8 (40%)	4 (25%)	2 (8.7%)
Other	3 (5.1%)	2 (10%)	1 (6.3%)	0
Prefer not to answer/no response	4 (6.8%)	3 (15%)	2 (12.6%)	0
Disability				
No	55 (93.2%)	18 (90%)	16 (100%)	21 (91.3%)
Yes	3 (5.1%)	2 (10%)	0	1 (4.3%)
Prefer not to answer	1 (1.7%)			1 (4.3%)
Academic Status				
FR	2 (3.4%)	1 (5%)	1 (6.3%)	0
SO	20 (33.9%)	8 (40%)	3 (18.8%)	9 (39.1%)
JR	18 (30.5%)	7 (35%)	5 (31.3%)	6 (26.1%)
SR	17 (28.8%)	4 (20%)	6 (37.5%)	7 (30.4%)
Other	2 (3.4%)		1 (6.3%)	1 (4.3%)
Major				
Engineering	33 (55.9%)	9 (45%)	5 (31.3%)	19 (82.6%)
Computer Science	20 (33.9%)	9 (45%)	7 (43.8%)	4 (17.4%)
Data Science	1 (1.7%)	1 (5%)	0	0
Physics	1 (1.7%)	0	1 (6.3%)	0
Other (2 dual majors)	4 (6.8%)	1 (5%)	3 (18.8%)	0
Expected Level of Education				
4 year degree	24 (40.7%)	9 (45%)	5 (31.3%)	10 (43.5%)
Masters' degree	24 (40.7%)	10 (50%)	10 (62.5%)	4 (17.4%)
Doctoral degree	9 (15.3%)	1 (5%)	0	8 (34.8%)
Post-doctoral Exp/Fellowship	1 (1.7%)		0	1. (4.3%)
Not reported	1 (1.7%)		1 (6.3%)	

Faculty and Teaching Assistants

A total of 12 responses (Faculty =4, TAs=8) were recorded for the pre-instruction survey. The typical instructor (faculty and TA) identified as male, Asian, non-Hispanic and not disclosing a disability. There are a total of nine (9) responses on the post-course survey. The typical post-respondent identified as male, non-Hispanic, African American and not disclosing a disability. In addition, participants reported the number of days they were involved in the course

	Pre Course Survey			Post-Course Survey		
Sample Characteristics	Overall Sample (N=12)	Faculty (n=4)	TAs (n=8)	Overall Sample (N=9)	Faculty (n=4)	TAs (n=5)
Gender (Pronoun)						
He	9(75%)	3(75%)	6(75%)	5(55.6%)	2 (50%)	3 (60%)
She	3(25%)	1(25%)	2(25%)	2(22.2%)	1 (25%)	1 (20%)
They				1(11.1%)	1 (25%)	0
Prefer not to answer				1(11.1%)	0	1 (20%)
Hispanic						
No	12 (100%)	4 (100%)	8 (100%)	8(88.9%)	4 (100%)	4 (80%)
Yes	0	0	0	0	0	0
Prefer not to answer	0	0	0	1(11.1%)	0	1 (20%)
Race						
Am. Indian/Alaskan Native	0	0	0	0	0	0
Asian or Pacific Islander	7 (58.3%)	2 (50%)	5 (62.5%)	3(33.3%)	1 (25%)	2 (40%)
Black or African American	4 (33.3%)	1 (25%)	3 (37.5%)	4(44.4%)	2 (50%)	2 (40%)
Nat Hawaiian or Pac Islander	0	0	0	0	0	0
White	1 (8.3%)	1 (25%)	0	2(22.2%)	1 (25%)	1 (20%)
Other	0	0	0	0	0	0
Prefer not to answer	0	0	0	0	0	0
Disability						
No	12 (100%)	4. (100%)	8 (100%)	5(55.5%)	2(75%)	3(60%)
Yes				0	0	0
Prefer not to answer				3(33.3%)	1(25%)	2(40%)
Participation -Number of Classes					M=5.5, SD=2.1, Range=3-8	M=31, SD=8.9, Range=20-40

Why did Students Enroll in the Course?

Students expect this Applied Machine Learning course to be valuable with 85% indicating that they expected the course to be helpful in getting an internship and 81% believing it would be helpful in getting a job. In addition 69% indicated that they wanted to learn more about machine learning and they would learn something useful for their other classes. While faculty and TAs also believed that this course would be helpful in getting internships and jobs, they most strongly believed students enrolled because they liked the applications of machine learning.

	Overall Student Sample (N=59)	Arkansas (n=20)	Kentucky (n=16)	Morgan State (n=23)	Faculty (n=4)	Teaching Assistants (n=8
Advisor encouragement	42%	25%	44%	57%	0%	63%
Like the applications of machine learning	46%	50%	50%	39%	100%	75%
Had nothing better to do with my time this summer	31%	30%	50%	17%	0%	0%
Peers were applying too	8%	20%	0%	4%	25%	13%
Curious to know what the Machine Learning was about	69%	65%	81%	65%	25%	38%
Had done other summer programs and this one looked different	10%	5%	19%	9%	0%	13)
Might learn something useful for my classes	69%	85%	69%	57%	25%	13%
Family encouragement	12%	5%	25%	9%	25%	0%
Would be helpful in getting me an internship	85%	85%	94%	78%	75%	38%
Would be helpful in getting a job	81%	85%	87%	74%	75%	38%
Would be helpful if/when applying to graduate degree programs	36%	40%	38%	30%	0%	25%
Recruited at my/their school	10%	0%	0%	26%	25%	0%
Wanted to learn something new	58%	60%	69%	48%	0%	25%
Wanted to be around others that like the same things I do	25%	35%	37%	9%	0%	0%
Interested in jobs related to machine learning	53%	55%	56%	48%	50%	25%
The course would help me/them figure out what to do in the future	56%	50%	63%	57%	25%	13%

Pre and Post Survey Measurement Scales

Students – Several scales were constructed from survey items included in the pre and post survey administrations. These scales included the applied machine learning course objectives and student learning outcomes (SLOs), ABET SLOs, Engineering efficacy, persistence, and career readiness. Overall, reliability estimates were very supportive, ranging from .762 to .956 on the pre and from .781 to .988 at post.

		Students		
Scale	**Items**	**Pre**	**Post**	**Description**
Applied ML Course Units/Topics	39	.939	.988	Confidence in knowledge and ability related to each topic in the course.
Applied ML SLOs	6	.806	.938	Confidence in knowledge and abilities related to student learning outcomes
Career Development Units	13	.950	.965	Confidence in knowledge and ability related to career development topics.
Career Readiness	8	.925	.921	Competencies for Career Readiness – National Association Of Colleges and Employers
Interest in ML Careers/Jobs	10	.909	.879	Interest in ML-related jobs/careers
ABET SLOs	11	.946	.972	Confidence in the knowledge and ability related to the ABET SLOs
Engineering Efficacy				Undergraduate Students' Engineering Self-Efficacy
General Knowledge and Ability	6	.924	.950	
Engineering Skills	5	.880	.948	
Engineering design	5	.949	.964	
Tinkering Skills	8	.956	.948	
Longitudinal Assessment of Engineering Efficacy	23	.892	.956	Longitudinal Assessment of Engineering Self-Efficacy
21st Century Skills	11	.911	.967	Confidence in relation to 21st century skills (e.g. teamwork, communication)
Intent to Persist	14	.864	.909	Persistence in degree and career
MSLQ- Critical Thinking	5	.821	.876	Critical Thinking skills
MSLQ-Self-Regulation	12	.762	.889	Self-regulation skills
MSLQ-Peer Learning	3	.797	.781	

Pre and Post Survey Measurement Scales

Faculty and Teaching Assistants – Several scales were also constructed from survey items included in the pre and post survey administrations. These scales included parallel versions of some offered to students (applied machine learning course SLO, course topics, career development and career readiness) as well as the Teaching Engineering Efficacy scales for faculty and the GTA Teaching Self-Efficacy Scale (GTA-TSES) and Teaching Assistants Self-Efficacy Scale (TSE) at TAs. Overall, reliability estimates were very supportive with all exceeding .950 on the pre. With the exception of two scales, all reliability estimates exceeded .75 on the posy survey.

		Faculty/TAs		
Scale	**Items**	**Pre**	**Post**	**Description**
Applied ML Course Units/Topics	39	.978	.965	Confidence in knowledge and ability related to each topic in the course.
Applied ML SLOs				
Confidence	6	.993	NA	Confidence related to SLOs
Alignment with Course	6	NA	.589	
Achievement by Students	6	NA	.848	
Career Development Units	13	.988	.924	Confidence in knowledge and ability related to career development topics.
Career Readiness	8	.990	.918	Competencies for Career Readiness – National Association Of Colleges and Employers
Faculty- Teaching Engineering Efficacy				
Content Knowledge	16	.993	.495	Efficacy in teaching content
Motivate Students	3	.983	.857	Efficacy to motivate students
Instructional Strategies	5	.986	.789	Efficacy to use instructional strategies
Engagement	4	.960	.960	Efficacy to engage students in class
Graduate Students				
GTA self efficacy scale	22	.991	.979	GTA efficacy related to TA duties
GTA Efficacy – Learning	11	.962	.987	Efficacy for creating learning environment
GTA Efficacy – Instructional	7	.930	.967	Efficacy for using instructional strategies

Summary of Daily and Weekly Feedback

Students were provided an opportunity for daily and weekly feedback throughout the course. A summary of these feedback of provided in the following pages. A complete record of their feedback, including specific comments and suggestions made by students can be found in the Appendix section of this report. A daily feedback opportunity was provided each day through week 4. In weeks 5 to 7, daily feedback was no longer requested on Fridays so students could focus of the weekly feedback request.

Week 1 – Responses during week 1 were overwhelmingly positive with all items ion each day averaging above 3.75 (using a 5-point scale). Students were especially in agreement that instructors demonstrated command of the content and that the teaching assistants were helpful. While the instructors command of content average above 4 each day, students were particularly positive of June 9 (M=4.60) versus June 8 (M=4.16). Overall, students participating from Morgan State less favorably compared to the other two sites. These responses were significantly lower in relation to the helpfulness of the teaching assistants, quality of instruction, perception of instructor's command of content, being able to keep up with the pace of the instruction and having a good understanding of what was addressed in class.

Week 2 – The daily feedback was very positive with all but two responses averaging above 4.0 (using a 5-point scale). Comparisons among days did reveal that students reported less understanding and were not as able to keep up with the pace on June 17 compared to the other days. Follow-up comparisons also revealed that students perceived the quality of instruction to be significantly higher on June 16 compared to June 15 or June 17. As with week 1, participants from Morgan State responded less positively, especially in comparison to students participating at the Kentucky site.

Week 3 - While this week's daily feedback was generally lower than the previous week, it was positive with all but three responses averaging above 3.5 (using a 5-point scale). Comparisons among days did reveal that students perceived the quality of instruction on June 22 to be significantly better than that of June 24. No significant differences were observed among the three sites this week. Descriptively, students from Morgan State provided the highest ratings in relation to quality of instruction and having a good understanding of what was addressed in class while students at Kentucky were most positive in terms of instructor's command of the content and helpfulness of the teaching assistants.

Week 4 - The week's feedback was most positive at the beginning of the week and generally declined as the week progressed. While all but 2 items averaged above 3.5 for the first 3 days, half of the items on July 1 averaged below 3.5 and one item averaged below 3. Comparisons among days did reveal that students perceived the quality of instruction on July 1 to be significantly lower than the previous 3 days. Students also reported having a significantly better understanding of the material on June 28 versus July 1. While no statistically significant differences were observed among the three sites, students from Kentucky reported the mot positive feedback in relation to instructor's commend of content, helpfulness of teaching assistants, overall quality of instruction, being actively engaged and having a good understanding of the day's class content.

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Week 5 - The week's feedback was generally positive with all items averaging above 3.5. Responses were most positive in relation to the instructors' command of content knowledge, the helpfulness of the teaching assistants and overall quality of instruction. Comparisons among days did not reveal any significant differences on the feedback items. Statistically significant different were observed when comparing the three sites with the responses from students at Kentucky being highest, especially in terms of the instructors command of the content, helpfulness of the TAs, and being actively engaged in the class.

Week 6 - The week's feedback was very positive with all items averaging a response above 4.0. Although comparisons among days did not reveal any statistically significant differences, student responses were especially positive in relation to instructors' command of content, overall quality of instruction and helpfulness of teaching assistants. Comparisons among the three sites did reveal statistically significant differences for all 6 items with students from the Morgan State site consistently responding less positively.

Week 7 - While the response rate was low this week, the feedback was very positive with all items generally averaging a response above 4.0. Student responses were especially positive in relation to instructors' command of content, overall quality of instruction and helpfulness of teaching assistants. Students also indicated that they were actively engaged in class each day with responses averaging from 4.05 (July 21) to 4.40 (July 22). The open-ended comments reflect students' appreciation for time to work on the capstone project in class this week. Few suggestions for improvement were offered. No comparisons were made among the three sites due to limited response from two of the sites.

Weekly Feedback

Students were provided an opportunity to submit weekly feedback for weeks 1 to 7. More specifically, feedback was requested in relation to the quality of instruction and professional development offered during the week. Students were also asked to indicate the level of confidence they had in their knowledge and skills pertaining the course topics and objectives scheduled to be addressed in class that week.

Instructional feedback – In general, feedback related to each week's instruction was very positive with overall average responses above 4.0 for 5 of the 7 weeks reported. More specifically, students responded most favorably in weeks 1 and 7 and least favorably in weeks 4 and 5. Students consistently indicated that instructors demonstrated command of the content and they would be able to use what they learned in class to complete the course projects with responses to these items averaging above 4.0 each of the seven weeks. In addition, students indicated that they were engaged, what they learned would help them in other courses, help them completed their degree, and prepare for a potential internship with average responses above 4.0 for all by one week (Week 5 – July 5-9). The two items that generally received the lowest response pertained to being able to keep up with the pace and having a good understanding of the week's content.

Weekly Professional Development feedback – Student response to the professional development was also very positive with overall averages ranging from 3.64 in week 6 to 4.34 in week 2. Students indicated each week that the presenter(s) were well-prepared, well-informed, and presentations were well-organized. In weeks 2 and 7, all items averaged above 4.0. These two week PD sessions were of great interest to students, helped them think about potential career opportunities, explore other PD options, prepare for potential internships, improve their preparation for and motivate them to have a successful career in Engineering.

Focus Groups - June 24, 25

Focus groups were conducted with students from each of the three institutions on June 25 and June 25. A sample of 7 students was invited to participate from each institution and each group was comprised on students from the same site for this initial round of focus groups. All focus groups were conducted virtually, using Zoom.
The primary purpose of these initial focus groups was to learn more from students about their experiences in the first few weeks of the course. More specifically, students were asked to discuss their experiences in the course thus far and the extent to which their experiences were as they expected. In doing so, students described aspects of the courses that were working well and offered some suggestions for what could be further examined in order to better serve students in the course.

Overall, students indicated that the overall course was "as advertised" as they described is as rigorous, intensive and fast-paced. They described the course environment as very collaborative and consistently indicated that one of the most beneficial aspects of the course has been meeting and working collaboratively with their peers. They generally perceived sessions in which a faculty member was present to be better that those they watched remotely. Some students expressed having greater challenges because of a more limited background and offered helpful suggestions.

Collaborative Environment – Working on projects and problems with peers has been very beneficial. Students describing meeting and working with other students from diverse backgrounds in terms of race, ethnicity, academic major and academic level. In each focus group, students described the opportunities they have to work with their peers have been most valuable. They described learning from each other as students in their groups have different backgrounds and offer different strengths. Several students described this collaborative teamwork experience as one preparing them for the real world in which they would work on projects as part of interdisciplinary teams.
The primary suggestion made related to collaboration is that they welcome more, especially opportunities to interact with students from other groups and the other sites. One group described a class in which the instructor integrated activities into the class that allowed students from the different sites to interact and work together. All groups would welcome more cross-site collaboration on projects and one group indicated interest in a "healthy" competition among the sites.

In-person is better than remote – At two sites, the instructional mode was mixed in that students spent approximately half the class days with an instructor at their site and the other half connecting virtually while students at the third site participate virtually every day as the instructor is at one of the other two sites. At both the mixed instructional sites, students described some technical and learner challenges associated with participating in the class virtually. They described technical issues related to being able to hear the instructor clearly or see the board when the video angle is focused on the classroom. If possible, a separate camera angle on the instructor or a mic for the instructor would help with this issue. Another issue they described is that they were less attentive and engaged when there is not an instructor in their room. The TAs are helpful but students described that they behave differently when an instructor is present.
Students at the virtual site described their experience as one in which they often feel disconnected. They indicated that it is difficult to follow remotely and the audio is often on mute when it appears that the instructor is talking with the class.

Instructional Methods -Student comments related to instructional approaches primarily regarded the amount of information covered in a class. Some students indicated that they have some difficulty keeping up as instructors work through many Powerpoint slides and all groups commented on the limited value of Powerpoint slides and a need for time to discuss more examples and applications. Overall, students welcome opportunities for more hands-on experiences and less Powerpoint slides and lectures.

More background would be helpful – Having more experience with programming, statistics and linear Algebra would be beneficial. Several students described that they struggled a bit to learn the necessary programming and other background skills to do the work in a timely manner. They described asking other students in the class and seeking online videos and resources to try and catch up on this ability. Students indicated that having more applied examples, resources, and additional non-graded assignments with feedback would be very helpful.

Course Management and Organization – Students, especially from one group, described the limitations of using Slack to navigate the course assignments, etc. They suggested using learning management systems (LMS) such as Canvas or Blackboard with which students are familiar, especially this past year as they completed most coursework online. There are helpful organizational features within these LMS such as a dashboard that alert participants (students, TAs and instructors) of the course schedule and when upcoming assignments are due. LMS also offer a way to organize course materials and store completed assignments and feedback that might be helpful to review when working on subsequent tasks.

Other Issues

Logistics and Expenses – Several students commented on a need for more advanced, detailed communication about the course/program and the logistics of transportation and enrollment. They described some minor issues arranging for transportation to the site and some students, particularly at one site, described a need to better understand what precise expenses for which they would be responsible.

Coordinated Activities outside of class - While students describing living and working together as a benefit, they also welcomed more coordinated social activities. Many students are not from the area and welcomed suggested and coordinated activities. One group described having optional social events planned (e.g. bowling, movies, dining, etc..) and thought this was a good opportunity for the class to get to know each other outside of the class context.

Instructor and Teaching Assistants – Pre and Post Findings

Machine Learning Student Learning Outcomes - Faculty were more confident in helping students meet the desired student learning outcomes, averaging 4 or above on each of them compared to TAs for which just 2 of the 6 SLOs averaged 4.0 or above. Both groups generally believe that the course was aligned with the expected SLOs with 4 of the 6 averaging 4.0 above for each group. The SLO pertaining to communication of technical aspects to an audience with limited background was identified as being least in alignment. Finally, TAs indicated higher levels of student achievement of the SLOs, identifying student ability to investigate, clean and visualize data as well was apply and tune common ML models while faculty most strongly identifying the communication of technical aspects and understanding and framing a problem as a supervised ML problem and

	Pre-Course Confidence		Alignment		Student Achievement	
	Faculty (n=4)	TA (n=7)	Faculty (n=4)	TA (n=5)	Faculty (n=4)	TA (n=5)
ML Course SLO	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
1- Investigate. clean and visualize data	4.75 (.50)	4.00 (1.53)	4.75 (.50)	4.60 (.55)	3.50 (.58)	4.20 (.45)
2- Understand and frame a problem as a supervised machine learning problem including whether it is a regression or classification problem and to incorporate the application	4.50 (.58)	3.86 (1.67)	3.33 (2.08)	4.40 (.55)	3.67 (.58)	4.00 (0.0)
3- Apply and tune common machine learning (ML) models in Python by making use of multiple ML toolkits	4.25 (.50)	3.71 (1.70)	5.00 (0.0)	4.60 (.55)	3.33 (.58)	4.20 (.45)
4- Demonstrate the ability to qualitatively and quantitatively evaluate the quality of trained regression and classification models	4.25 (.96)	3.71 (1.60)	4.67 (.58)	4.60 (.55)	3.00 (0.0)	4.00 (0.0)
5- Communicate technical concepts (oral and written) for an audience who may have limited technical background	4.25 (.50)	4.00 (1.53)	3.67 (1.15)	3.80 (.84)	3.67 (.58)	3.80 (.45)
6- Identify the potential bias in ML models and explain its implications	4.00 (.82)	3.50 (1.76)	5.00 (0.0)	4.00 (.71)	3.00 (0.0)	4.00 (.71)
Scale (1=Not at all, 5=A great extent)						

Machine Learning Units and Topics

Faculty and TAs were also asked to indicate the extent to which they confident in helping students acquire the knowledge and ability related to each of the units and topics to be addressed in the Applied Machine Learning Course. Faculty expressed the greatest confidence in helping students with functions, straight line equation, normal distribution properties, clustering, k-means models, probability and statistics and regular expressions. Teaching assistants expressed the most confidence in their ability to help with computer science and functions, followed by the straight line equation, matrix algebra, probability and p-values, visualization of data, and activation functions. At the post, faculty and TAs were asked to indicate the extent to which they were involved with each of the course topics. With the exception of two topics, Data Science and Ethical Consequences of ML, TAS indicated higher levels of involvement.

	Faculty - Confidence (n=4)		TAs Confidence (n=7)		Faculty - Involvement (n=2)		TAs Involvement (n=5)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Computer Science	4.50	.577	4.83	.408	3.50	.707	4.20	.837
Python	4.00	.816	4.29	1.254	3.50	.707	4.60	.548
Straight Line Equation	4.75	.500	4.43	1.134	2.00	1.414	4.20	.837
Functions	4.75	.500	4.86	.378	2.50	.707	4.20	.837
Matrix Algebra	4.50	.577	4.43	.976	2.50	.707	4.00	1.000
Normal Distribution Properties	4.75	.500	4.29	.756	2.00	1.414	3.80	.837
Hypothesis Testing	4.50	1.000	4.29	.951	2.00	1.414	3.60	.894
Probability and p-values	4.25	.957	4.43	.787	2.50	2.121	3.60	.894
Data Science	4.50	.577	4.29	.951	4.50	.707	4.00	1.000
Types of Machine Learning (ML) Models	4.50	.577	4.29	.951	4.00	.000	4.20	1.095
Ethical Consequences of Machine Learning	4.00	.816	4.14	.900	4.50	.707	3.80	1.304
Data Analysis and Manipulation - Colab notebooks	4.00	.816	4.29	.951	4.00	.000	4.00	.707
Data Analysis and Manipulation -Panda Series and Panda DataFrames	4.00	.816	4.00	1.155	3.50	.707	4.00	.707

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Visualization of data	4.25	.957	4.43	.787	3.00	1.414	4.20	.837
Acquiring and downloading data	4.50	.577	4.29	.951	3.50	2.121	4.20	.837
Exploratory data analysis	4.50	.577	4.29	1.113	4.50	.707	4.00	.707
Regression analysis	4.50	1.000	4.00	1.000	2.50	2.121	4.20	.837
Using scikit-learn for regression analysis	4.00	.816	4.00	1.414	2.50	2.121	4.00	1.000
Using TensorFlow	4.00	.816	3.71	1.380	1.50	.707	4.20	1.095
Binary Classification methods	4.25	.957	4.14	1.215	2.00	1.414	4.00	1.000
Multiclass Classification	4.25	.957	4.14	1.215	1.50	.707	4.00	1.000
Image - Video Classification	3.25	1.258	4.29	1.113	2.00	1.414	3.80	.837
Deep Learning	3.50	1.291	4.29	1.113	3.00	2.828	4.00	.707
Recurrent Neural Network	4.00	.816	4.29	.951	3.00	2.828	4.20	.837
Natural Language Processing	3.75	.957	4.00	1.155	3.00	2.828	4.00	1.000
Transfer Learning	3.50	1.000	4.14	.900	3.00	2.828	4.00	1.000
Clustering	4.75	.500	4.29	.951	1.00	.000	4.00	1.000
k-Means models	4.75	.500	4.14	1.215	2.50	2.121	4.00	1.000
Embedding	3.75	1.258	4.14	.900	2.50	2.121	4.00	1.000
Decision Trees and Random Forest	4.50	.577	4.14	.900	1.00	.000	3.60	.894
Bayesian Modeling	3.75	1.500	3.71	1.254	1.00	.000	3.60	.894
Support Vector Machines (SVM)	4.00	1.155	4.17	1.169	1.50	.707	3.80	1.095
XG Boost	3.75	1.500	3.71	1.254	1.00	.000	3.80	1.095
Activation Functions	3.75	1.258	4.43	.787	2.00	1.414	3.20	1.483
Big O	4.50	.577	3.86	1.215	1.00	.000	2.80	1.095
Dimensionality Reduction	4.25	.957	3.86	1.215	1.00	.000	3.00	1.225
Loss Functions	4.00	1.155	3.86	1.215	1.00	.000	3.20	1.483
Probability and Statistics	4.75	.500	4.14	.690	2.50	2.121	3.80	.837
Regular Expressions	4.75	.500	4.57	.535	3.00	.000	3.00	1.225
Scale (1=Not at all, 5= A great extent)								

Job Search and Career preparation Skills

Career development is a unit with this course and students will be engaged in activities aimed to better prepare students with the skills they need to get a job and begin their career. While faculty expressed greater confidence, both faculty and TAs indicated a moderately high levels of confidence with items generally averaging above 3.5 (using a 5-point scale). Faculty were especially confident in their ability to help students with thing like constructing a resume, giving and receiving feedback, preparing for a job interview, interviewing and preparing a presentation. TAs were most comfortable helping with preparing for a presentation, delivering an oral presentation with confidence and giving, receiving and using feedback. At the end of the course, faculty and TAs were generally less optimistic that they had an impact with TAS expressing higher levels of confidence. Teaching assistants did, however, indicate improved confidence in helping students give and receive feedback, prepare presentations and deliver strong oral presentations.

	Faculty PRE (n=4)		TAs PRE (n=7)		Faculty POST (n=3)		TAs POST (n=5)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Constructing a resume	4.50	.577	3.71	1.496	1.00	.000	2.20	1.304
Meeting and engaging with professionals in your field	4.50	.577	3.67	1.506	2.00	1.000	2.40	1.342
Giving feedback to others	4.50	.577	3.86	1.345	1.33	.577	4.00	1.000
Receiving and using feedback from others	4.25	.500	3.86	1.345	1.67	1.155	4.20	.837
Working with recruiters or career services related to potential jobs	3.75	.957	3.43	1.397	1.33	.577	2.20	1.304
Talking with faculty and others about potential internship of job opportunities	4.25	.500	3.71	1.496	2.33	1.528	3.60	.548
Preparing application materials for an internship or job	4.25	.500	3.71	1.380	1.67	1.155	2.20	1.095
Preparing for a job interview	4.50	.577	3.43	1.397	1.67	1.155	2.20	1.095
Interviewing for an internship or job	4.50	.577	3.43	1.272	1.67	1.155	2.20	1.095
Preparing for a presentation	4.75	.500	4.00	1.414	2.00	1.000	4.20	.837
Delivering a strong oral presentation with confidence	4.25	.500	3.86	1.345	2.00	1.000	4.40	.548
Learning about sources for potential internships or jobs	4.00	.816	3.43	1.397	2.00	1.732	2.60	.894
Applying for an internship or job opportunity	4.00	.816	3.57	1.397	1.67	1.155	2.80	1.095
1=Not at all, 5=A great extent								

Career Readiness Competencies

Faculty and TAs were asked to indicate their confidence in helping students with the eight competencies of career readiness in the table below. Overall, faculty were more confident in helping students become career ready, but both groups were very confident in their ability with responses to all 8 competencies below averaging above 3.5. While faculty reported less confidence on the post-course survey, TAs confidence to help students in terms of career readiness remained stable or was higher. TAs were especially confident that they helped students with their teamwork, technology, communication and critical thinking skills.

	Faculty - PRE (n=4)		TAs - PRE(n=7)		Faculty - POST (n=3)		TAs - POST(n=5)	
Career Readiness Competencies	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Career and Self-Development - Awareness of strengths and weaknesses and seek relationships with professionals and opportunities to better prepare you for a career.	4.00	.816	3.71	1.380	2.33	1.528	3.60	.548
Communication - Able to clearly exchange information, ideas, facts, and perspectives wit people inside and outside of my current institution or organization.	4.00	.816	3.71	1.380	2.33	1.528	4.00	.707
Critical Thinking - Identify and respond to needs based upon an understanding of the context and a logical analysis of relevant information.	4.25	.957	3.71	1.380	3.67	1.528	4.00	.707
Equity and Inclusion - Demonstrate an awareness, attitude, knowledge, and skills required to equitably engage and include people from different cultures.	4.25	.957	3.86	1.464	3.00	2.000	3.80	.447
Leadership - Recognize and Capitalize on personal and team strengths to achieve organizational goals.	4.00	.816	3.86	1.464	2.33	1.528	3.80	.837
Professionalism - Knowing work environments differ greatly, understand and demonstrate effective work habits, and act in the interest of the larger community and workplace.	4.25	.500	3.86	1.464	2.67	1.528	3.80	.447
Teamwork - Build and maintain collaborative relationships to work effectively toward common goals, while appreciating diverse viewpoints and share responsibilities.	4.25	.957	3.86	1.464	2.33	.577	4.20	.837
Technology - Understand and leverage technology ethically to enhance efficiency, complete tasks and accomplish goals.	4.25	.500	3.86	1.464	3.33	2.082	4.20	.837

Faculty - Teaching Engineering Self-Efficacy

Faculty responded to items related to their confidence (self-efficacy) in their abilities related to teaching engineering. Their responses are summarized below. In general, faculty indicated they have moderate levels of confidence at the beginning of the course as most items tended to average near or above the scale midpoint of 3. Faculty responded with greatest confidence to items related to engaging students with an overall scale mean of 3.5 on the pre and M=4.58 at the end of the course, followed by Engineering content knowledge (M=3.15 on pre, M=4.62 on post), instructional self-efficacy (M=3.10 pre, M=4.33 post) and motivational self-efficacy (M=3.0 pre, M=4.08 post). Reponses to all items at the end of the course were higher with just 2 of the 29 items below 4.0.

	Pre (n=4)		Post (n=4)	
Teaching Engineering Self-Efficacy Scales and Items	Mean	SD	Mean	SD
Engineering content knowledge self-efficacy	3.15	1.48	4.62	.31
I can explain the different aspects of the engineering design process.	3.25	1.708	4.67	.577
I can discuss how given criteria affect the outcome of an engineering project.	3.25	1.708	4.67	.577
I can explain engineering concepts well enough to be effective in teaching engineering.	3.50	1.732	4.67	.577
I can assess my students' engineering products	3.25	1.500	4.33	.577
I know how to teach engineering concepts effectively.	3.25	1.500	4.33	.577
I can craft good questions about engineering for my students.	3.50	1.732	4.67	.577
I can employ engineering activities in my classroom effectively.	3.25	1.500	4.67	.577
I can discuss how engineering is connected to students' daily lives.	3.25	1.500	4.67	.577
I can spend the time necessary to plan engineering lessons for my class.	2.50	1.291	3.67	1.528
I can explain the ways that engineering is used in the world.	3.50	1.732	4.67	.577
I can describe the process of engineering design.	3.25	1.708	4.33	.577
I can select appropriate materials for engineering activities.	3.00	1.414	4.33	.577
I can create engineering activities at the appropriate level for my students.	2.75	1.500	4.33	.577
I stay current in my knowledge of engineering.	3.25	1.500	4.33	.577
I can recognize and appreciate the engineering concepts as they apply to other content areas.	2.75	1.500	5.00	.000
I can guide my students' solution development with the engineering design process.	3.00	1.414	4.67	.577

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Faculty - Teaching Engineering Self-Efficacy

(Continued from Page 17)

	Pre (n=4)		Post (n=4)	
	Mean	SD	Mean	SD
Motivational self-efficacy	3.00	1.66	4.08	.42
I can motivate students who show low interest in the class.	2.75	1.500	4.00	1.000
I can increase students' interest in learning engineering	3.25	1.708	4.25	.500
Through engineering activities, I can make students enjoy the class more.	3.00	1.826	4.00	.000
Instructional self-efficacy	3.10	1.41	4.33	.43
I can use a variety of assessment strategies for teaching engineering.	3.00	1.414	3.67	.577
I can adequately assign my students to work at group activities like engineering.	3.25	1.500	4.00	1.000
I can plan engineering lessons based on each student's learning level.	3.00	1.414	4.67	.577
I can gauge student comprehension of the engineering materials that I have taught	3.00	1.414	4.25	.500
I can help my students apply their engineering knowledge to real world situations.	3.25	1.500	4.75	.500
Engagement self-efficacy	3.50	1.67	4.58	.72
I can promote a positive attitude toward learning engineering in my students.	3.75	1.893	5.00	.000
I can encourage my students to think creatively during class or other engineering activity.	3.50	1.732	4.33	1.155
I can encourage students to think critically when practicing engineering.	3.50	1.732	4.33	1.155
I can encourage students to interact and collaborate with each other when working on engineering activities.	3.25	1.708	4.67	.577
1=Not at all, 5=A great extent				

Graduate Teaching Assistant Efficacy

Graduate teaching assistants (GTAs) responded to items reflecting their confidence in creating a positive learning environment and being able to implement effective instructional approaches. TAs indicated increasing high levels of confidence in their abilities related to creating a positive learning environment (M=4.37 on pre and M=4.58 on post) and using instructional strategies (M=4.28 at pre and M=4.51 at post).

	Pre (n=8)		Post (n=5)	
	Mean	SD	Mean	SD
Learning Environment	4.37	.64	4.58	.52
Promote student participation in class	3.88	1.246	4.40	.548
Make students aware that I have a personal investment in them and their learning	4.38	.518	4.40	.548
Create a positive classroom climate for learning	4.50	.535	4.60	.548
Think of my students as active learners	4.63	.518	4.60	.548
Encourage students to ask questions in class	4.38	.518	4.60	.548
Actively engage students in class activities	4.25	.886	4.60	.548
Promote a positive attitude toward learning in my students	4.38	.744	4.60	.548
Provide support and encouragement for students who are having difficulty	4.50	.756	4.50	.577
Encourage students to interact and work collaboratively with each other	4.38	.744	4.60	.548
Show students respect through my actions	4.50	.756	4.40	.548
Encourage students to take initiative for their own learning	4.38	.744	4.40	.548
Instructional Strategies	4.28	.57	4.51	.50
Appropriately grade student assignments	4.38	.744	4.60	.548
Accurately evaluate student academic ability	4.13	.641	4.60	.548
Prepare instructional materials to be used in class	4.25	.463	4.60	.548
Spend sufficient time planning for class	4.38	.744	4.60	.548
Clearly identify course objectives and expected student outcomes	4.13	.641	4.40	.548
Provide students with detailed feedback about their progress in class	4.37	.744	4.40	.548
Stay current in my knowledge of the content	4.37	.744	4.60	.548
1=Not at all, 5=A great extent				

GTA Efficacy

The table below summarizes GTA's level of confidence in their teaching ability. Overall, they expressed moderately high levels of confidence as all items averaged 3.5 or higher and 14 of the 22 items averaged 4.0 or higher at the beginning of the course and all items averaging above 4.0 at the end of the course. At the beginning of the course, TAs were especially confidence in their ability to give lab demonstrations, averaging above 4.5 (M=4.63). However, at the end of the course, they expressed a very high level of confidence in all items with 19 of the 22 averaging above 4.5.

	Pre (n=8)		Post (n=5)	
	Mean	SD	Mean	SD
State clear outcomes for the class	4.25	.463	4.60	.548
Motivate student interest in the class	4.25	.707	4.60	.548
Communicate at a level that matches students' ability to comprehend	4.25	1.389	4.60	.548
Give a lecture	3.75	1.282	4.20	.837
Give a lab demonstration	4.63	.518	4.40	.548
Respond to student questions during a class, lab or tutorial session	4.25	1.389	4.60	.548
Respond to students' answers during class, labs or tutorial session.	4.13	1.356	4.60	.548
Plan an organized lecture	3.88	1.246	4.00	1.225
Provide constructive written feedback on student assignments	4.00	1.414	4.60	.548
Use technology effectively in class	4.00	1.309	4.60	.548
Assign grades to student work	3.88	1.356	4.60	.548
Manage student disagreements	3.63	1.188	4.60	.548
Model problem solving skills for students	3.88	1.356	4.60	.548
Ask open, stimulating questions to generate discussion	3.88	1.356	4.60	.548
Prepare visual aids for instruction	3.88	1.356	4.60	.548
Arrange for constructive peer feedback and suggestions to improve your teaching	4.00	1.309	4.60	.548
Use gestures or other non-verbal behavior effectively when teaching	4.00	1.309	4.60	.548
Handle disruptive behavior	3.88	1.356	4.60	.548
Encourage student participation in class and other activities	4.00	1.309	4.60	.548
Use student feedback to improve your teaching	4.13	1.356	4.60	.548
Think about your teaching and make necessary changes to improve	4.00	1.309	4.60	.548
Overall, I am confident in my ability to carry out my responsibilities as a teaching assistant	4.00	1.309	4.60	.548
1-Not at all, 5=A great extent				

Open-ended Questions

Three pre-course open-ended questions were included to gain more information related to what faculty and TAs expected students to learn in the courses, and challenges they anticipated for students and themselves. These responses are summarized in the tables.

Describe specific knowledge or skills what you expect students to gain from this cou	
Faculty (n=2)	**TAs (n=1)**
- Foundation Machine Learning and Deep Learning - Python programing skills -Understanding what they can and cannot do with machine learning	I expect students to learn from coursework and engage in the program. From the the students should walk away with valuable hands-on experience, knowledge f and professors, as well as insight into graduate school, industry, research, and ac

Describe any challenges you anticipate for students during this course.	
Faculty (n=2)	**TAs (n=1)**
-I expect students with minimal programming knowledge to fall behind. - Programming skills - Deep Learning	The swift nature of this course can be difficult. The student's main challe the material and time management for ultimate success in the class.

Describe any challenges you anticipate for yourself during this course.	
Faculty (n=2)	**TAs (n=1)**
-I expect it to be challenging to deliver a consistent experience across all sites. - Background Diversity of the class	The swift nature of this course can be difficult. For myself, staying up coursework and being versed in various topics will be challenging.

Post Course Responses

At the conclusion of the course, faculty and TAS were asked to describe modifications made to the course, challenges experiences and observed student outcomes. Faculty describe the need to supplement the course curriculum with additional information, resources and examples for students and some topics needed more time dedicated to them.

Please describe ways in which you had to modify the course and what needs to be added		
Faculty Modifications	**Reasons for Modifications**	**Course Additions**
1- On many of the topics, additional information regarding how to implement (code) functionalities was needed. In some cases, additional examples were necessary. **2-** Provide the link between the current lecture and the previous lectures - Recap the previous lectures, especially the lectures that are related to the current lecture - Provide more examples with visualization - When explaining the theory, the corresponding code will be provided to show how to implement that concept. - At the end of the lecture, there is a recap section as well as provide the link to the next lecture - For some problems such as regression, classification, etc, provide pseudo code (step-by-step) **3-** I completely redid two of the days. The base lectures were made for in person discussion and it needed more animations and information for discussion over zoom.	**1-** I would have more modifications, if I had to do it again. I am not sure the degree of modifications I made changes the outcome significantly. With all the above additional parts, here are what students comments (as well as I observed) **2-** With recap and linkage lectures: without those, the students feel lost. The additional information aims to systematically understanding the whole picture of the course - With examples and visualization: Aim to understand some new concepts or terminologies much better - With example code to illustrate some theory concept: Aim to know how to implement some new concepts using python/ tensorflow. Help to student be ready for the colab section **3-** Hopefully the additions made it easier for students to understand the information.	**1-** The students I interacted with needed as much experience and practice with Python as possible. Few of the students I interacted with knew how to use the Google Credits for additional Computational resources. Perhaps a brief tutorial would help with that. **2-** Deep learning is a hard topic, it will be better to break into 2 weeks instead of 1 week. **3-** I added embedding information and notes to the NLP lecture.

Describe any challenges you had working with students during this course	
Faculty (n=2)	**TAs (n=2)**
• I thought the hybrid format made content delivery a challenge. In addition, I was concerned that there were numerous students who were so behind after 3 weeks (in terms of concepts) that they didn't benefit from the latter parts of the course. The different levels of experience coming into AMLI was a significant challenge. • It was difficult to understand what the workload already assigned to students and when they should complete activities.	• Some of the students are not enough skilled in programming. So it was really challenging to teach them and make understand how to do coding in Tensorflow and other machine learning library. • program debugging

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Post Course Responses

(Continued from Page 22)

Describe specific knowledge or skills that you observed students gain from this course	
Faculty – no responses	TAs (n=2)
	Working in a team, basic steps of research, which problems can be solved by machine learning/ deep learning. Programming skills, Python programming, machine learning, team work, critical thinking

Describe ways in which this summer course experience has benefited you as an instructor and how you will apply what you gained in the coming year.	
Faculty (n=1)	TAs (n=1)
This was my first in person lecture in a year. It was good talking to many diverse students.	This summer course help me to improve my communication skill with students which will be beneficial for me in the long run.

Please describe what advice you have for other instructors or teaching assistants planning to teach this course.	
Faculty (n=1)	TA – no response
Use the existing material as a starting point not a blue point.	

Student Findings

Pre-Course Student Confidence in Machine Learning Student Learning Outcomes

As might be expected, students were not very confident in their knowledge and abilities related to the Applied Machine Learning Course student learning outcomes prior to course instruction. These will be examined again at the end of the course to determine improvement in their confidence.

	Overall Sample (N=59)		Arkansas (n=20)		Kentucky (n=16)		Morgan State (n=23)	
ML Course SLO	Mean	SD	Mea n	SD	Mea n	SD	Mean	SD
	2.01	.804	2.13	.835	1.53	.551	2.23	.816
Investigate. clean and visualize data	2.72	1.360	3.11	1.323	2.00	1.155	2.91	1.379
Understand and frame a problem as a supervised machine learning problem including whether it is a regression or classification problem and to incorporate the application requirements	1.72	1.022	1.79	1.084	1.31	.602	1.96	1.147
Apply and tune common machine learning (ML) models in Python by making use of multiple ML toolkits	1.52	1.013	1.53	.905	1.19	.544	1.74	1.287
2.13Demonstrate the ability to qualitatively and quantitatively evaluate the quality of trained regression and classification models	1.69	.995	1.58	.692	1.13	.342	2.17	1.267
Communicate technical concepts (oral and written) for an audience who may have limited technical background	2.71	1.389	2.95	1.433	2.06	1.389	2.96	1.261
Identify the potential bias in ML models and explain its implications	1.71	.973	1.95	1.224	1.50	.730	1.65	.885
Scale (1=Not at all, 5=A great extent)								

Pre-Course Confidence in ABET Student Learning Outcomes

At the beginning of the course, students did express a moderately high level of confidence in the knowledge and ability related to the ABET student learning outcomes as all responses averaged above the scale midpoint of 3. Students were especially confident in their ability to communicate effectively (M=4.25), understand their professional and ethical responsibilities (M=4.14), recognize the need and ability to engage in professional development/improvement (M=4.08) and work effectively on multidisciplinary teams (M=4.08).

	Overall Sample (N=59)		Arkansas (n=20)		Kentucky (n=16)		Morgan State (n=23)	
ABET SLO	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	3.79	.857	3.85	.860	3.56	.891	3.91	.835
Apply knowledge of mathematics, science and engineering	3.73	.925	3.80	.951	3.31	.873	3.96	.878
Design and conduct experiments and interpret the resulting data	3.50	.941	3.60	1.046	3.20	1.014	3.61	.783
Design a system, component, or process to meet desired needs	3.10	1.227	3.15	1.268	2.75	1.125	3.30	1.259
Work effectively on a multidisciplinary team	4.08	1.164	4.15	1.089	3.94	1.340	4.13	1.140
Identify, formulate and solve engineering problems	3.56	1.071	3.85	1.089	3.31	1.078	3.48	1.039
Understand professional and ethical responsibility	4.14	.880	4.20	.768	4.06	.929	4.13	.968
Communicate effectively	4.25	.939	4.30	.865	4.00	.966	4.39	.988
Understand the broad impact of engineering solutions in a global, economic, environmental and social context	3.76	1.135	3.70	1.081	3.50	1.211	4.00	1.128
Recognize the need for and ability to engage in professional development/ improvement	4.08	1.022	4.10	1.021	4.00	.894	4.13	1.140
Understanding and awareness of contemporary issues	3.78	1.131	3.60	1.095	3.69	1.138	4.00	1.168
Ability to use the techniques, skills, and modern engineering tools necessary for engineering practice.	3.73	1.172	3.85	1.182	3.38	1.408	3.87	.968
Scale (1=Not at all, 5=A great extent)								

Pre-Course Confidence in Machine Learning Units and Topics

Students were asked to indicate the extent to which they confident in their knowledge and ability related to each of the units and topics to be addressed in the Applied Machine Learning Course. Consistent with their confidence in the overall student learning outcomes, students were not very confident in their knowledge and abilities related to the specific content in the course prior to course instruction. These will be examined again at the end of the course to determine improvement in their confidence.

	Overall Sample (N=59)		Arkansas (n=20)		Kentucky (n=16)		Morgan State (n=23)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	1.74	.495	1.80	.557	1.55	.369	1.81	.499
Computer Science	2.73	1.229	2.90	1.334	2.63	1.025	2.65	1.301
Python	2.34	1.183	2.35	1.268	2.06	.998	2.52	1.238
Straight Line Equation	2.74	1.596	3.05	1.701	2.80	1.699	2.43	1.441
Functions	3.34	1.226	3.60	1.536	3.25	1.065	3.17	1.029
Matrix Algebra	2.54	1.104	2.80	1.196	2.25	1.065	2.52	1.039
Normal Distribution Properties	2.61	1.236	2.80	1.322	2.40	.986	2.59	1.333
Hypothesis Testing	2.84	1.211	2.90	1.334	2.87	.990	2.78	1.278
Probability and p-values	2.69	1.188	2.70	1.174	2.40	1.183	2.87	1.217
Data Science	1.83	1.045	1.89	1.100	1.25	.447	2.17	1.154
Types of Machine Learning (ML) Models	1.31	.730	1.35	.489	1.06	.250	1.45	1.057
Ethical Consequences of Machine Learning	1.53	1.030	1.80	1.196	1.31	.793	1.45	1.011
Data Analysis and Manipulation - Colab notebooks	1.37	.807	1.45	.759	1.13	.342	1.48	1.039
Data Analysis and Manipulation -Panda Series and Panda DataFrames	1.34	.779	1.35	.813	1.13	.342	1.48	.947
Visualization of data	2.12	1.176	2.20	1.196	1.38	.619	2.57	1.237
Acquiring and downloading data	2.31	1.273	2.26	1.195	1.94	1.181	2.61	1.373
Exploratory data analysis	1.85	1.096	1.95	1.099	1.31	.602	2.13	1.254
Regression analysis	1.80	1.047	2.00	1.214	1.44	.727	1.87	1.058
Using scikit-learn for regression analysis	1.15	.407	1.25	.444	1.06	.250	1.13	.458
Using TensorFlow	1.09	.283	1.16	.375	1.06	.250	1.04	.209
Binary Classification methods	1.44	.702	1.45	.826	1.44	.727	1.43	.590
Multiclass Classification	1.30	.658	1.26	.562	1.07	.267	1.48	.846

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Pre-Course Confidence in Machine Learning Units and Topics

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Image - Video Classification	1.44	.794	1.50	.827	1.06	.250	1.65	.935
Deep Learning	1.57	1.061	1.47	.964	1.19	.403	1.91	1.345
Recurrent Neural Network	1.21	.526	1.16	.375	1.13	.342	1.32	.716
Natural Language Processing	1.31	.598	1.20	.410	1.13	.342	1.55	.800
Transfer Learning	1.31	.730	1.30	.923	1.13	.342	1.45	.739
Clustering	1.46	.857	1.45	.999	1.25	.577	1.61	.891
k-Means models	1.28	.586	1.40	.754	1.13	.352	1.26	.541
Embedding	1.38	.875	1.40	.995	1.38	1.025	1.36	.658
Decision Trees and Random Forest	1.29	.617	1.50	.827	1.13	.342	1.22	.518
Bayesian Modeling	1.12	.375	1.25	.550	1.06	.250	1.04	.209
Support Vector Machines (SVM)	1.09	.283	1.15	.366	1.06	.250	1.05	.213
XG Boost	1.07	.254	1.10	.308	1.06	.250	1.04	.209
Activation Functions	1.20	.550	1.15	.489	1.13	.342	1.30	.703
Big O	1.56	.952	1.90	1.165	1.62	.885	1.22	.671
Dimensionality Reduction	1.14	.345	1.20	.410	1.19	.403	1.04	.209
Loss Functions	1.22	.457	1.30	.571	1.13	.342	1.22	.422
Probability and Statistics	2.62	1.211	2.40	1.231	2.60	1.183	2.83	1.230
Regular Expressions	2.22	1.378	2.00	1.338	1.94	1.289	2.61	1.438
Scale (1=Not at all, 5= A great extent)								

Pre-Course Engineering Self-Efficacy

In general, students indicated moderately high levels of confidence related to engineering with all items averaging above the scale midpoint of 3. At the beginning of this course, students were especially confident that they can learn what is taught in their engineering-related courses (M=4.41), do good work in their major classes (M=4.38) and earn good grades in their engineering-related courses (M=4.34).

	Overall Sample (N=59)		Arkansas (n=20)		Kentucky (n=16)		Morgan State (n=23)	
Engineering Self-Efficacy	Mean	SD	Mean	SD	Mean	SD	Mean	SD
General Self-Efficacy	4.18	.696	4.22	.655	3.92	.746	4.32	.676
I can master the content in my major courses	4.14	.899	4.10	1.071	4.00	.816	4.26	.810
I can master the content in even the most challenging engineering course	3.73	1.080	3.80	1.005	3.13	1.258	4.09	.848
I can do good work in my major coursework	4.38	.721	4.45	.605	4.25	.775	4.41	.796
I can do an excellent job on engineering-related problems or tasks I am assigned	4.10	.759	4.20	.616	3.94	.854	4.13	.815
I can learn the content taught in my engineering-related courses	4.41	.673	4.40	.598	4.25	.683	4.52	.730
I can earn good grades in my engineering-related courses	4.34	.739	4.35	.745	4.00	.845	4.57	.590
Engineering Skills Self-Efficacy	4.02	.762	3.80	.931	3.99	.706	4.24	.587
I can perform experiments independently	3.76	1.006	3.55	1.191	3.69	.873	4.00	.905
I can analyze data from experiments	3.97	.955	3.74	1.098	3.87	.885	4.22	.850
I can orally communicate results from experiments	4.07	.962	3.80	1.105	4.00	1.155	4.35	.573
I can communicate results in written form	4.14	.819	3.80	1.105	4.31	.602	4.30	.559
I can solve problems using a computer	4.20	.867	4.15	.933	4.06	.998	4.35	.714

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Pre-Course Engineering Self-Efficacy

(Continued from Page 28)

Design Self-Efficacy	3.75	.889	3.48	.909	3.62	.872	4.07	.813
I can design new things	3.85	.979	3.60	.995	3.81	.981	4.09	.949
I can identify a design need	3.84	.922	3.50	.946	3.93	.917	4.09	.848
I can develop design solutions	3.71	1.001	3.35	1.040	3.50	1.033	4.17	.778
I can evaluate a design	3.68	1.025	3.45	1.050	3.44	1.031	4.04	.928
I can reorganize changes needed for a design solution to work	3.71	.929	3.50	1.000	3.56	.892	4.00	.853
Tinkering Self-Efficacy	3.68	1.03	3.45	1.13	3.46	1.02	4.02	.89[illegible]
I can work with tools and use them to build things	4.00	1.034	3.85	1.040	3.88	1.088	4.22	.99[illegible]
I can work with tools and use them to fix things	3.90	1.078	3.85	.988	3.56	1.263	4.17	.98[illegible]
I can work with machines	3.61	1.273	3.25	1.585	3.50	1.155	4.00	.95[illegible]
I can fix machines	3.20	1.243	2.90	1.373	3.13	1.147	3.52	1.1[illegible]
I can manipulate components and devices	3.36	1.224	3.05	1.395	3.19	1.109	3.77	1.0[illegible]
I can assemble things	3.73	1.243	3.45	1.317	3.50	1.317	4.13	1.0[illegible]
I can disassemble things	3.88	1.171	3.84	1.259	3.56	1.263	4.13	1.0[illegible]
I can apply technical concepts in engineering	3.80	1.063	3.50	1.192	3.38	1.088	4.35	.64[illegible]
Scale (1=SD,2=D, 3=N, 4=A, 5=SA)								

Pre-Course Longitudinal Assessment of Engineering Self-Efficacy

Students expressed high levels of efficacy in response to the LAESE items with responses averaging above 4 on 18 of the 23 items. Students most strongly agreed that they would complete their degree at their current institution (M=4.80). They also indicated that they are able to make friends with people with different backgrounds and values (M=4.69), they expect to do well in their courses this year (M=4.59) and a degree in engineering will allow them to get a well-paying job (M=4.59).

	Overall Sample (N=59)		Arkansas (n=20)		Kentucky (n=16)		Morgan State (n=23)	
LAESE Items	Mean	SD	Mea n	SD	Mean	SD	Mean	SD
	4.32	.473	4.42	.444	4.22	.481	4.33	.496
I can relate to people around me in my classes	4.10	.824	4.00	.918	4.06	.998	4.22	.600
I can succeed in an engineering degree program	4.51	.704	4.70	.470	4.31	.873	4.48	.730
I have a lot in common with other students in my classes	3.93	.785	3.90	.718	4.00	.816	3.91	.848
Someone like me can succeed in an engineering career	4.41	.833	4.50	.688	4.06	1.181	4.57	.590
The other students in my classes share my personal interests	3.75	.779	3.95	.887	3.44	.727	3.78	.671
I can succeed in an engineering program while NOT having to give up participation in my outside interests (e.g. family, friends, extracurricular activities)	3.76	1.179	3.75	1.333	3.38	1.310	4.04	.878
I can relate to people around me in my extracurricular activities	3.95	.899	4.00	1.076	3.87	.885	3.96	.767
I can complete the math requirements for my degree program,	4.54	.750	4.75	.444	4.25	1.065	4.57	.662

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Pre-Course Longitudinal Assessment of Engineering Self-Efficacy

(Continued from Page 30)

A degree in engineering will allow me to obtain a well paying job	4.59	.746	4.70	.470	4.50	.816	4.57	.896
I will do well in my major courses this year	4.59	.673	4.60	.598	4.38	.719	4.74	.689
I will complete my degree at my current institution	4.80	.446	4.90	.308	4.69	.479	4.78	.518
A degree in engineering will give me the kind of lifestyle I want	4.44	.856	4.50	.688	4.25	.856	4.52	.994
I can make friends with people from different backgrounds and/or values	4.69	.534	4.75	.444	4.81	.403	4.57	.662
Doing well in my classes will increase my sense of self-worth	4.41	.859	4.45	.999	4.40	.737	4.39	.839
I will feel "part of the group" on my job if I enter engineering	3.78	1.052	4.00	.918	3.50	.816	3.78	1.278
I can complete the science (e.g. physics, chemistry) requirements for my degree	4.60	.724	4.68	.478	4.56	1.031	4.57	.662
Taking advance math courses will help keep my career options option	4.25	.843	4.15	1.040	4.19	.834	4.39	.656
A degree in engineering will allow me to get a job where I can use my talents and creativity	4.46	.803	4.50	.761	4.53	.640	4.36	.953
I can persist in engineering this academic year.	4.46	.837	4.75	.444	4.25	.775	4.35	1.071
I can approach a faculty or staff member to get assistance when needed.	4.20	.846	4.40	.821	4.06	.929	4.13	.815
I can adjust to new work or learning environments	4.47	.679	4.60	.598	4.50	.632	4.35	.775
A degree in engineering will allow me to get a job I like	4.36	.905	4.65	.671	4.44	.629	4.04	1.147
Scale (1=SD,2=D, 3=N, 4=A, 5=SA)								

Pre-Course Confidence in 21st Century Skills

Students expressed high levels of confidence in their ability in their 21st century skills, especially regarding their respect for the differences of their peers (M=4.75, their confidence in working with students from different backgrounds (M-4.69), include others' perspectives when making decisions (M=4.59).

	Overall Sample (N=59)		Arkansas (n=20)		Kentucky (n=16)		Morgan State (n=23)	
Efficacy - 21st Century Skills	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	4.47	.545	4.54	.358	4.33	.685	4.51	.576
I am confident I can lead others to accomplish a goal.	4.29	.832	4.25	.716	4.19	.981	4.39	.839
I am confident I can encourage others to do their best.	4.41	.790	4.55	.605	4.38	.885	4.30	.876
I am confident I can produce high quality work.	4.51	.704	4.60	.503	4.44	.892	4.48	.730
I am confident I can respect the differences of my peers.	4.75	.544	4.85	.489	4.63	.619	4.74	.541
I am confident I can help my peers.	4.31	.856	4.25	.786	4.06	1.124	4.52	.665
I am confident I can include others' perspectives when making decisions.	4.59	.619	4.60	.754	4.69	.479	4.52	.593
I am confident I can make changes when things do not go as planned.	4.47	.751	4.70	.571	4.37	.719	4.35	.885
I am confident I can set my own learning goals.	4.47	.799	4.60	.503	4.13	1.246	4.57	.590
I am confident I can manage my time wisely when working on my own.	4.20	.906	4.15	.875	3.94	1.124	4.43	.728
When I have many assignments, I can choose which ones need to be done first.	4.51	.817	4.65	.489	4.06	1.181	4.70	.635
I am confident I can work well with students from different backgrounds.	4.69	.595	4.75	.550	4.75	.447	4.61	.722
Scale (1=SD,2=D, 3=N, 4=A, 5=SA)								

Pre-Course Persistence

Students generally indicated a strong intention to persist. More specifically, they indicated that they planned to take courses in their major next year (M=4.78) and complete their current degree (M=4.78). They also strongly intended to get a job in their current discipline (M=4.60)..

	Overall Sample (N=59)		Arkansas (n=20)		Kentucky (n=16)		Morgan State (n=23)	
Intention to Persist	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
	4.01	.571	4.05	.536	3.98	.549	4.00	.635
Next year, I plan to take courses in my major discipline	4.78	.559	4.90	.308	4.88	.342	4.61	.783
I intend to get my degree in my current major	4.78	.494	4.90	.308	4.75	.447	4.70	.635
I am sure that I will continue my education in my major field	4.49	.917	4.75	.550	4.31	1.250	4.39	.891
I intend to get an advanced degree in my major field	3.86	1.252	3.75	1.517	3.75	1.238	4.04	1.022
I plan to pursue and secure an internship this	4.29	.929	4.20	1.105	4.44	.629	4.26	.964
I intend to get a job in my major field	4.60	.674	4.85	.366	4.50	.816	4.45	.739
I can see myself working in my current field for at least 5 years.	4.39	.851	4.75	.550	4.19	.911	4.22	.951
I plan to devote my career to my current major discipline	4.22	.892	4.65	.587	4.00	1.033	4.00	.905
I plan to take additional courses related to machine learning.	3.93	.944	3.60	.940	4.00	1.033	4.17	.834
I intend to seek internship opportunities related to machine learning	4.03	.830	3.95	.759	3.94	.929	4.17	.834
I am considering changing my major to something more directly related to machine	2.73	1.298	2.70	1.455	2.50	1.265	2.91	1.203
I plan to pursue an advanced degree related to machine learning	3.10	1.282	2.70	1.380	3.25	1.438	3.35	1.027
I plan to get a job related to machine learning.	3.39	1.034	3.40	.940	3.38	1.258	3.39	.988
I would like to have a career related to machine learning	3.56	.952	3.55	.945	3.81	1.047	3.39	.891
1=Not TRUE of me , 5=VERY TRUE of me								

Pre-Course Confidence in Career Development and Preparation

In general, students expressed confidence in their abilities as they prepare for a career with all but one item averaging above the scale midpoint. They indicated the greatest confidence in their abilities related to having high ethical standards (M=4.36), teamwork skills (M=4.33) and their cultural awareness (M=4.22). Areas in which there is room for improvement included security knowledge (M=2.77), entrepreneurship and intrapreneurship (M=3.22) and data interpretation and visualization (M=3.25).

	Overall Sample (N=59)		Arkansas (n=20)		Kentucky (n=16)		Morgan State (n=23)	
Confidence in Career Development	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Good communication skills	3.96	1.122	4.11	.937	3.81	1.047	3.95	1.356
Knowledge of physical science and engineering fundamentals	3.24	.999	3.16	.958	3.13	.806	3.40	1.188
Ability to identify, formulate, and solve engineering problems	3.46	.966	3.47	1.020	3.40	.737	3.50	1.100
Curiosity and persistent desire for continuous learning	4.16	.898	4.42	.769	4.19	1.047	3.90	.852
Self-drive and motivation	4.19	.933	4.56	.705	3.94	1.06	4.05	.945
Cultural awareness in the broad sense (nationality, ethnicity, gender, sexual orient.)	4.22	.786	4.42	.769	4.19	.655	4.05	.887
Ability to make good economic and business judgements and decisions	3.72	1.054	3.74	1.098	3.44	1.209	3.95	.848
High ethical standards	4.36	.847	4.42	1.017	4.37	.619	4.30	.865
Critical thinking skills	4.02	.913	4.11	.937	3.81	.911	4.10	.912
Willingness to task calculated risks	3.73	1.027	3.89	.994	3.44	1.153	3.80	.951
Ability to prioritize efficiently	4.07	.900	4.42	.902	3.88	.806	3.90	.912
Project management	3.80	1.043	4.11	1.150	3.50	1.095	3.75	.851
Teamwork skills	4.33	.862	4.53	.612	4.25	1.000	4.20	.951
Entrepreneurship and intrapreneurship	3.22	1.134	3.11	1.150	2.81	1.167	3.65	.988
Ability to use new technology	4.13	.818	4.26	.806	4.00	.816	4.10	.852
Applied knowledge of eng core sciences	3.45	1.068	3.32	1.376	3.44	.892	3.60	.883
Data interpretation and visualization skills	3.25	1.158	3.32	1.250	2.69	1.078	3.65	.988

Pre-Course Job Search and Career Preparation Skills

Career development is a unit with this course and students will be engaged in activities aimed to better prepare them with the skills they need to get a job and begin their career. In response to these items, students indicated a high level of confidence with all items averaging above 3.5 (using a 5-point scale). Students expressed the most confidence in their ability to receive and use feedback from others (M=4.07) and construct a resume (M=4.0). They also indicated confidence in their ability to talk with faculty about potential internships or jobs (M=3.81), and prepare application materials for an internship of job (M=3.81).

	Overall Sample (N=59)		Arkansas (n=20)		Kentucky (n=16)		Morgan State (n=23)	
	Mean	SD	Mean	SD	Mea n	SD	Mean	SD
	3.79	.747	**3.86**	.777	**3.60**	.686	**3.87**	.772
Constructing a resume	4.00	.795	4.20	.951	3.88	.500	3.91	.811
Meeting and engaging with professionals in your field	3.62	1.023	3.95	.999	3.00	.966	3.77	.922
Giving feedback to others	3.88	.880	3.90	.852	3.75	1.065	3.95	.785
Receiving and using feedback from others	4.07	.951	4.21	.855	3.94	1.237	4.05	.805
Working with recruiters or career services related to potential jobs	3.71	.929	3.63	1.012	3.63	.885	3.86	.910
Talking with faculty and others about potential internship of job opportunities	3.81	1.017	3.70	1.081	3.87	.957	3.86	1.08
Preparing application materials for an internship or job	3.81	1.025	4.00	1.106	3.56	1.094	3.82	.907
Preparing for a job interview	3.64	.931	3.70	1.129	3.38	.719	3.77	.869
Interviewing for an internship or job	3.72	.951	3.85	1.137	3.44	.892	3.82	.795
Preparing for a presentation you will do	3.76	1.048	3.85	1.182	3.50	1.033	3.86	.941
Delivering a strong oral presentation with confidence	3.79	1.039	3.80	1.105	3.56	1.153	3.95	.899
Learning about sources for potential internships or jobs	3.69	.977	3.60	1.142	3.63	.957	3.82	.853
Applying for an internship or job opportunity	3.81	.963	3.85	1.137	3.69	.946	3.86	.834
1=Not at all, 5=A great extent								

Pre-Course Career Readiness Competencies

Students were asked to indicate their confidence in relation to the eight competencies of career readiness in the table below. Overall, students expressed confidence in their abilities, especially in terms of teamwork (M=4.32), equity and inclusion (M=4.27) and professionalism (M=4.21).

	Overall Sample (N=59)		Arkansas (n=20)		Kentucky (n=16)		Morgan State (n=23)	
Career Readiness Competencies	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	4.10	.738	4.21	.711	4.09	.593	4.02	.866
Career and Self-Development - Awareness of strengths and weaknesses and seek relationships with professionals and opportunities to better prepare you for a career.	4.04	.801	4.00	.882	4.00	.730	4.09	.811
Communication - Able to clearly exchange information, ideas, facts, and perspectives wit people inside and outside of my current institution or organization.	4.11	1.012	4.21	.918	4.13	.957	4.00	1.15
Critical Thinking - Identify and respond to needs based upon an understanding of the context and a logical analysis of relevant information.	3.96	.906	4.26	.872	3.75	.775	3.86	.990
Equity and Inclusion - Demonstrate an awareness, attitude, knowledge, and skills required to equitably engage and include people from different cultures.	4.27	.842	4.37	.895	4.53	.516	4.00	.926
Leadership - Recognize and Capitalize on personal and team strengths to achieve organizational goals.	4.05	.915	4.26	.872	3.94	.929	3.95	.950
Professionalism - Knowing work environments differ greatly, understand and demonstrate effective work habits, and act in the interest of the larger community and workplace.	4.21	.868	4.21	1.032	4.31	.602	4.14	.910
Teamwork - Build and maintain collaborative relationships to work effectively toward common goals, while appreciating diverse viewpoints and share responsibilities.	4.32	.834	4.42	.769	4.33	.816	4.23	.922
Technology - Understand and leverage technology ethically to enhance efficiency, complete tasks and accomplish goals.	3.93	1.006	3.95	1.026	3.87	.957	3.95	1.07
1-Not at all, 5=A great extent								

Pre-Course Career Interests

Finally, students were asked to indicate their interest in specific careers related to machine learning. Of the 10 careers listed below, students expressed the greatest interest in software engineering (M=3.74), software development (M=3.63), software programming (M=3.58) and machine learning engineering (M=3.58).

	Overall Sample (N=59)		Arkansas (n=20)		Kentucky (n=16)		Morgan State (n=23)	
Career Interests	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	3.42	.909	3.61	.963	3.36	.794	3.28	.951
Software Engineer	3.74	1.173	3.80	1.240	3.88	1.360	3.57	.978
Software Programmer	3.58	1.281	3.70	1.342	3.81	1.377	3.29	1.146
Software Developer	3.63	1.342	3.85	1.387	3.87	1.356	3.24	1.261
Data Scientist	3.18	1.311	3.60	1.465	2.94	1.237	2.95	1.161
Computer Engineer	3.33	1.185	3.35	1.424	3.25	1.125	3.38	1.024
Artificial Intelligence Research Scientist	3.48	1.321	3.55	1.468	3.50	1.317	3.40	1.231
Cloud Engineer	3.21	1.107	3.45	1.050	2.93	1.335	3.19	.981
Machine Learning Scientist	3.37	1.244	3.60	1.314	3.38	1.360	3.15	1.089
Machine Learning Engineer	3.58	1.068	3.65	1.137	3.63	1.147	3.48	.981
Big Data Engineer	3.05	1.216	3.55	1.191	2.38	.885	3.10	1.261
1=Not at all interested, 5=Very interested								

Students - Post Survey Findings

Sample - A total of 61 students responded to the post survey. Of these 59 were matched up to their corresponding pre survey. The post results are summarized in this next section followed by a comparison from pre to post for the matched sample of students.

What do you think you gained as a result of your participation in this Applied Machine Learning course?

- Students were asked to identify what they gained from their experiences in this Applied Machine Learning course. Just 10% indicated that they were not sure and 8 of the 10 remaining statements were selected by over 75% of the students completing the course. More specifically, students indicated that they learned applications of machine learning (90%), gained experience that would be helpful in getting an internship (90%), gained valuable knowledge of machine learning (89%), networked with other students in their discipline (87%), gained experience helpful in getting a job (84%), learned things useful for other courses (82%), gained experience helpful when applying to graduate programs (80%) and established valuable contacts and relationships with faculty in their discipline (79%). In general, a lower percentage of students at Morgan State identified specific benefits and they were more likely to indicate that they were not sure.

	Overall Sample (N=61)	Arkansas (n=21)	Kentucky (n=17)	Morgan State (n=23)
	Percentage	Percentage	Percentage	Percentage
I learned about the applications of machine learning	.90	1.00	1.00	.74
I gained valuable knowledge related to machine learning	.89	1.00	1.00	.70
I learned something useful for my other classes	.82	.86	.88	.74
I gained experience that will be helpful in getting me an internship	.90	.90	1.00	.83
I gained experience that will be helpful in getting a job	.84	.90	.94	.70
This experience will be helpful if/when applying to graduate degree programs	.80	.86	.88	.70
I networked with other students in my discipline	.87	.90	1.00	.74
I became more interested in a career related to machine learning	.61	.57	.76	.52
The course helped me figure out what I want to do in the future	.67	.67	.88	.52
I established valuable contacts and relationships with faculty in my discipline	.79	.81	1.00	.61
I'm not sure	.10	.00	.12	.17

Retrospective Pre-Post Assessment

Students were asked to examine a list of attributes and indicate the extent to which they experienced change since the beginning of the course. Responses were very positive with all averaging above 3.75 and 11 of the 15 above 4.0. Students reported great improvement in their confidence to complete their degree (M=4.2) and earn an advanced degree or get a job after graduation (M=4.3). They also reported great improvement in their communication skills (M=4.23), problem-solving ability (M=4.26) and ability to work effectively with others (M=4.28). Overall, the greatest change (improvement) was reported from Kentucky with an average of 4.38, which was significantly higher that that reported from Morgan State, averaging 3.85.

	Overall Sample (N=61)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=23)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	4.06	.641	4.03	.616	4.38	.468	3.85	.699
Interest in machine learning	4.03	.966	4.14	.910	4.47	.624	3.61	1.076
Belief I will succeed in school	4.11	.877	4.05	.865	4.59	.618	3.83	.937
Awareness of potential careers in machine learning	4.10	.768	4.19	.680	4.41	.618	3.78	.850
Ability to work effectively with others	4.28	.777	4.19	.750	4.59	.618	4.13	.869
Ability to engage in problem-solving	4.26	.794	4.29	.717	4.65	.493	3.96	.928
Communication skills	4.23	.716	4.24	.700	4.29	.686	4.17	.778
Leadership ability	4.08	.787	4.10	.831	4.00	.707	4.14	.834
Ability to think of creative solutions to real issues	4.07	.854	4.05	.805	4.29	.686	3.91	.996
Time management skills	3.89	.755	3.86	.854	4.12	.697	3.74	.689
Interest in a ML career	3.82	1.025	3.76	1.091	4.12	.928	3.65	1.027
Use of effective study skills	3.87	.806	3.67	.730	4.29	.772	3.74	.810
Intention to enroll in more ML related courses	3.82	1.049	3.80	.951	4.35	.786	3.43	1.161
Intention to seek internship or other opportunities related to machine learning	3.85	1.030	3.71	1.056	4.35	.702	3.61	1.118
Commitment to complete my degree.	4.20	.872	4.14	.910	4.53	.624	4.00	.953
Confidence that I will get a job or an advanced degree upon graduation.	4.30	.869	4.33	.796	4.59	.507	4.05	1.090

Scale (1=Much Worse, 2 = Worse, 3= About the same, 4= Better, 5= Much Better)

Post Course Reflections

At the end of the course, students were asked to reflect on their experiences and indicate their level of agreement with the statements summarized in the table below. Overall, students planned to keep in touch with other students from the course (M=4.51) and valued the residential component (M=4.43). They also established strong relationships with faculty and planned to keep in touch (M=4.23) and believed they were better prepared for the coming year (M=4.28). Finally, getting a stipend was important to them (M=4.41).

	Overall Sample (N=61)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=23)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	4.09	.587	4.14	.571	4.34	.403	3.84	.639
It was very important to me that I received course credit for this course	4.20	.980	4.38	.740	4.29	1.213	3.96	.976
Getting a stipend was important to me.	4.41	.883	4.76	.539	4.06	1.298	4.35	.647
I found the residential experience to be very enjoyable	4.43	.784	4.67	.577	4.71	.470	4.00	.953
I would enroll in a refresher course if available	3.79	1.018	4.00	.949	4.00	1.000	3.43	1.037
I am more likely to join a professional organization now	3.97	.894	3.76	.944	4.47	.624	3.78	.902
I plan to keep in touch with other students I met in this course.	4.51	.698	4.62	.669	4.71	.470	4.26	.810
I established strong relationships with the faculty from this course and will keep in touch.	4.23	.739	4.24	.831	4.41	.795	4.09	.596
I will keep in touch with the teaching assistants from this course.	3.72	1.002	3.67	1.197	3.88	.857	3.65	.935
I plan to continue work on the capstone project from this course.	3.21	1.213	3.10	1.338	3.65	1.169	3.00	1.087
I am interested in other learning opportunities to help me retain what I learned in this course.	4.15	.928	4.24	.944	4.65	.493	3.70	.974
I would recommend other coursework related to machine learning to my peers.	4.16	.820	4.10	.768	4.71	.470	3.83	.887
I will be better prepared for the coming year after completing this course.	4.28	.819	4.19	.814	4.65	.606	4.09	.900
Scale- (1=SD, 2=D, 3=N, 4=A, 5=SA)								

Confidence in Machine Learning Student Learning Outcomes -

Students indicated moderate to high levels of confidence in their knowledge and abilities related to the Applied Machine Learning Course student learning outcomes, with average responses all above the midpoint, ranging from 3.48 to 3.88. These were all much higher compared to the beginning of the course when responses all averaged below 3, ranging from 1.52 to 2.72. A matched samples comparison will be reported later in this report.

	Overall Sample (N=61)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=23)	
ML Course SLO	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	3.63	.935	3.68	1.21	3.71	.715	3.51	.807
Investigate. clean and visualize data	3.88	1.059	3.71	1.231	4.13	.885	3.87	1.01
Understand and frame a problem as a supervised machine learning problem including whether it is a regression or classification problem and to incorporate the application requirements	3.57	1.040	3.52	1.209	3.76	.903	3.48	.994
Apply and tune common machine learning (ML) models in Python by making use of multiple ML toolkits	3.48	1.089	3.52	1.327	3.65	.996	3.30	.926
Demonstrate the ability to qualitatively and quantitatively evaluate the quality of trained regression and classification models	3.48	1.026	3.62	1.284	3.41	.712	3.39	.988
Communicate technical concepts (oral and written) for an audience who may have limited technical background	3.70	1.174	3.76	1.446	3.71	1.105	3.65	.982
Identify the potential bias in ML models and explain its implications	3.64	1.033	3.95	1.203	3.59	1.064	3.39	.783
Scale (1=Not at all, 5=A great extent)								

Confidence in ABET Student Learning Outcomes

Students were confident in the knowledge and ability related to the ABET student learning outcomes as all responses averaged above 3.75, with 7 of the 11 above 4.0. Students were especially confident in their ability to communicate effectively (M=4.13), work on an interdisciplinary team (M=4.13), understand their professional and ethical responsibilities (M=4.13), understand the broader impact of engineering (M=4.08) and understanding and awareness of contemporary issues (M=4.08).

	Overall Sample (N=61)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=23)	
ABET SLO	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	4.02	.789	4.03	.986	4.34	.549	3.79	.678
Apply knowledge of mathematics, science and engineering	4.00	.876	4.14	.964	4.12	.857	3.78	.795
Design and conduct experiments and interpret the resulting data	3.98	.904	4.10	.944	4.24	.831	3.70	.876
Design a system, component, or process to meet desired needs	3.82	.992	3.81	1.123	4.12	.781	3.61	.988
Work effectively on a multidisciplinary team	4.13	.885	4.29	.845	4.41	.712	3.78	.951
Identify, formulate and solve engineering problems	3.92	.862	4.00	1.000	4.18	.728	3.65	.775
Understand professional and ethical responsibility	4.13	.866	4.14	1.062	4.47	.514	3.87	.815
Communicate effectively	4.13	.806	4.05	1.071	4.41	.618	4.00	.603
Understand the broad impact of engineering solutions in a global, economic, environmental and social context	4.08	.936	4.00	1.183	4.41	.712	3.91	.793
Recognize the need for and ability to engage in professional development/ improvement	4.07	.854	3.95	1.024	4.59	.507	3.78	.736
Understanding and awareness of contemporary issues	4.08	.900	4.00	1.049	4.53	.624	3.83	.834
Ability to use the techniques, skills, and modern engineering tools necessary for engineering practice.	3.92	.962	3.81	1.167	4.29	.849	3.73	.767
Scale (1=Not at all, 5=A great extent)								

Confidence in Machine Learning Units and Topics

Students indicated moderate to high levels of confidence in their knowledge and ability related to units and topics to be addressed in the Applied Machine Learning Course with average responses ranging from 2.59 (Dimensionality Reduction) to 3.87 (Visualization of Data). All averages were higher than that reported at the beginning of the course and a pre-post comparison for the overall matched sample is summarized later in this report.

	Overall Sample (N=61)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=23)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	3.28	.904	3.32	1.15	3.48	.479	3.08	.891
Computer Science	3.49	1.120	3.52	1.289	3.82	.728	3.22	1.166
Python	3.51	1.135	3.52	1.365	3.88	.697	3.22	1.126
Straight Line Equation	3.43	1.372	3.33	1.623	3.76	1.348	3.26	1.137
Functions	3.73	1.177	3.71	1.419	4.06	.899	3.50	1.102
Matrix Algebra	3.31	1.162	3.48	1.401	3.06	1.088	3.35	.982
Normal Distribution Properties	3.27	1.133	3.30	1.380	3.41	.870	3.13	1.100
Hypothesis Testing	3.38	1.106	3.43	1.399	3.53	.874	3.23	.973
Probability and p-values	3.28	1.121	3.38	1.359	3.29	.849	3.18	1.097
Data Science	3.28	.993	3.38	1.284	3.47	.514	3.05	.950
Types of Machine Learning (ML) Models	3.39	1.005	3.38	1.203	3.65	.786	3.22	.951
Ethical Consequences of Machine Learning	3.80	1.062	3.90	1.261	4.12	.697	3.48	1.039
Data Analysis and Manipulation - Colab notebooks	3.75	1.150	3.76	1.446	4.29	.588	3.35	1.027
Data Analysis and Manipulation -Panda Series and Panda DataFrames	3.75	1.135	3.86	1.315	4.12	.600	3.39	1.196
Visualization of data	3.87	1.087	3.86	1.276	4.35	.606	3.52	1.082
Acquiring and downloading data	3.85	1.138	3.81	1.289	4.35	.702	3.52	1.163
Exploratory data analysis	3.70	1.101	3.62	1.359	4.06	.748	3.52	1.039
Regression analysis	3.49	1.090	3.76	1.261	3.59	.870	3.17	1.029
Using scikit-learn for regression analysis	3.39	1.215	3.62	1.284	3.59	.870	3.04	1.331
Using TensorFlow	3.26	1.079	3.33	1.278	3.59	.795	2.96	1.022
Binary Classification methods	3.61	1.100	3.62	1.203	4.00	.791	3.30	1.146
Multiclass Classification	3.36	1.126	3.29	1.271	3.82	.883	3.09	1.083

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Confidence in Machine Learning Units and Topics

(Continued from Page 43)

Image - Video Classification	3.21	1.156	3.38	1.322	3.59	1.004	2.78	.998
Deep Learning	3.20	1.108	3.24	1.300	3.53	1.007	2.91	.949
Recurrent Neural Network	3.11	1.097	3.14	1.276	3.47	.874	2.83	1.029
Natural Language Processing	3.02	1.008	3.05	1.203	3.24	.903	2.83	.887
Transfer Learning	2.97	1.025	3.05	1.191	3.24	.831	2.70	.974
Clustering	3.03	1.008	3.25	1.118	3.12	.928	2.78	.951
k-Means models	3.08	.996	3.20	1.196	3.24	.831	2.87	.920
Embedding	3.02	1.066	3.05	1.234	3.18	.951	2.87	1.014
Decision Trees and Random Forest	3.16	1.003	3.10	1.179	3.59	.712	2.91	.949
Bayesian Modeling	2.90	1.091	2.90	1.261	2.82	.883	2.96	1.107
Support Vector Machines (SVM)	2.84	1.067	2.90	1.300	2.82	.809	2.78	1.043
XG Boost	2.90	1.012	2.90	1.179	2.94	.827	2.87	1.014
Activation Functions	3.03	1.169	3.00	1.449	3.18	.883	2.96	1.107
Big O	2.72	1.082	2.67	1.390	2.65	.931	2.83	.887
Dimensionality Reduction	2.59	1.101	2.71	1.347	2.41	.939	2.61	.988
Loss Functions	2.75	1.174	2.81	1.401	2.75	1.125	2.70	1.020
Probability and Statistics	3.18	1.162	3.29	1.384	3.12	.928	3.13	1.140
Regular Expressions	3.05	1.117	3.00	1.378	3.12	.928	3.04	1.022
Scale (1=Not at all, 5= A great extent)								

Engineering Self-Efficacy

Overall, students indicated high levels of confidence related to engineering with all but 5 of the 24 items averaging above 4.0 (using a 5-point scale. Responses on the post-course survey were also generally higher than those reported at the beginning of the course. At the end of this course, students were especially confident in their general and skill-related abilities. More specifically, they strongly believed that they could learn the content taught in engineering classes (M-4.35), earn good grades in these courses (M=4.34), do good work in engineering courses (M=4.30), solve problems using computers (M=4.28), and analyze data from experiments (M=4.26).

	Overall Sample (N=61)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=23)	
Engineering Self-Efficacy	Mean	SD	Mean	SD	Mean	SD	Mean	SD
General Self-Efficacy	4.26	.782	4.28	.921	4.34	.604	4.19	.787
I can master the content in my major courses	4.30	.919	4.38	1.071	4.35	.702	4.17	.937
I can master the content in even the most challenging engineering course	4.05	.956	4.14	.964	4.12	.857	3.91	1.041
I can do good work in my major coursework	4.30	.863	4.24	.995	4.47	.624	4.22	.902
I can do an excellent job on engineering-related problems or tasks I am assigned	4.25	.789	4.29	.845	4.29	.686	4.17	.834
I can learn the content taught in my engineering-related courses	4.35	.777	4.29	.956	4.44	.629	4.35	.714
I can earn good grades in my engineering-related courses	4.34	.929	4.33	1.017	4.41	.618	4.30	1.063
Engineering Skills Self-Efficacy	4.23	.817	4.22	.959	4.45	.493	4.09	.867
I can perform experiments independently	4.15	.946	4.05	1.161	4.35	.606	4.09	.949
I can analyze data from experiments	4.26	.835	4.24	.889	4.53	.717	4.09	.848
I can orally communicate results from experiments	4.23	.938	4.29	1.056	4.35	.702	4.09	.996
I can communicate results in written form	4.25	.809	4.29	.902	4.35	.702	4.13	.815
I can solve problems using a computer	4.28	.951	4.24	1.091	4.65	.493	4.04	1.022
Design Self-Efficacy	4.08	.933	3.96	1.13	4.34	.669	3.98	.904
I can design new things	4.08	1.038	3.86	1.236	4.47	.717	4.00	1.000
I can identify a design need	4.16	.986	3.95	1.203	4.53	.624	4.09	.949
I can develop design solutions	4.07	.964	3.95	1.071	4.29	.772	4.00	1.000

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Engineering Self-Efficacy

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I can evaluate a design	4.03	1.016	4.00	1.183	4.24	.752	3.91	1.041
I can reorganize changes needed for a design solution to work	4.03	.983	4.05	1.203	4.18	.883	3.91	.848
Tinkering Self-Efficacy	3.91	.941	3.83	1.04	4.11	.911	3.85	.884
I can work with tools and use them to build things	4.05	.973	3.95	1.071	4.29	.772	3.96	1.022
I can work with tools and use them to fix things	4.10	1.044	4.05	1.161	4.35	.862	3.96	1.065
I can work with machines	3.92	1.085	3.71	1.271	4.18	1.015	3.91	.949
I can fix machines	3.68	1.157	3.60	1.188	3.65	1.272	3.78	1.085
I can manipulate components and devices	3.74	1.168	3.71	1.189	3.94	1.298	3.61	1.076
I can assemble things	3.90	1.115	3.71	1.231	4.24	1.200	3.82	.907
I can disassemble things	3.92	1.085	3.95	1.161	4.06	1.088	3.78	1.043
I can apply technical concepts in engineering	4.03	.966	4.05	1.024	4.18	.951	3.91	.949
Scale (1=SD,2=D, 3=N, 4=A, 5=SA)								

Longitudinal Assessment of Engineering Self-Efficacy

Students maintained high levels of efficacy in response to the LAESE items throughout the course with responses averaging above 4 on 21 of the 23 items. Students most strongly agreed that they were able to make friends with people of different backgrounds (M=4.59), they would complete their degree at their current institution (M=4.58), they were able to adjust to new working environments (M=4.55), and they would succeed in an engineering career (M=4.48). Overall, students from Kentucky reported significant higher levels of confidence (M=4.39) compared to students from Morgan State (M=4.09).

	Overall Sample (N=61)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=23)	
LAESE Items	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	4.32	.565	4.39	.614	4.52	.382	4.09	.574
I can relate to people around me in my classes	4.25	.869	4.33	.913	4.35	.862	4.09	.848
I can succeed in an engineering degree program	4.36	.684	4.48	.602	4.59	.618	4.09	.733
I have a lot in common with other students in my classes	4.20	.872	4.14	.964	4.53	.624	4.00	.905
Someone like me can succeed in an engineering career	4.48	.725	4.57	.676	4.71	.470	4.23	.869
The other students in my classes share my personal interests	4.17	.867	4.14	.964	4.47	.624	3.95	.899
I can succeed in an engineering program while NOT having to give up participation in my outside interests (e.g. family, friends, extracurricular activities)	3.95	1.126	4.10	1.221	4.06	1.197	3.73	.985
I can relate to people around me in my extracurricular activities	4.18	.813	4.29	.784	4.41	.618	3.91	.921
I can complete the math requirements for my degree program,	4.38	.783	4.57	.676	4.35	.862	4.23	.813
Doing well in math will enhance my career/job opportunities	4.32	.792	4.29	.845	4.59	.507	4.14	.889
A degree in engineering will allow me to obtain a well paying job	4.48	.725	4.62	.669	4.71	.470	4.18	.853
I will do well in my major courses this year	4.47	.650	4.48	.680	4.71	.470	4.27	.703
I will complete my degree at my current institution	4.58	.619	4.62	.590	4.76	.437	4.41	.734
A degree in engineering will give me the kind of lifestyle I want	4.32	.860	4.43	.746	4.59	.618	4.00	1.04

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Longitudinal Assessment of Engineering Self-Efficacy

(Continued from Page 47)

I can make friends with people from different backgrounds and/or values	4.59	.668	4.62	.669	4.88	.485	4.35	.714
Doing well in my classes will increase my sense of self-worth	4.28	.859	4.43	.811	4.59	.712	3.91	.900
I will feel "part of the group" on my job if I enter engineering	3.89	.915	3.90	1.044	3.94	.899	3.83	.834
I can complete the science (e.g. physics, chemistry) requirements for my degree	4.39	.737	4.52	.680	4.47	.624	4.22	.850
Taking advance math courses will help keep my career options option	4.21	.897	4.33	.913	4.41	.795	3.96	.928
A degree in engineering will allow me to get a job where I can use my talents and creativity	4.28	.819	4.43	.746	4.47	.800	4.00	.853
I can persist in engineering this academic year.	4.34	.772	4.48	.750	4.47	.800	4.13	.757
I can approach a faculty or staff member to get assistance when needed.	4.33	.676	4.33	.730	4.47	.624	4.22	.671
I can adjust to new work or learning environments	4.55	.622	4.57	.676	4.76	.437	4.36	.658
A degree in engineering will allow me to get a job I like	4.42	.743	4.52	.680	4.76	.437	4.05	.844
Scale (1=SD,2=D, 3=N, 4=A, 5=SA)								

Confidence in 21st Century Skills -

Students continued to express high levels of confidence in their ability in their 21st century skills, especially regarding their confidence in respecting the differences in their peers (M=4.48), working with students from different backgrounds (M-4.47), confidence in their ability to help peers (M=4.47), and include others' perspectives when making decisions (M=4.43). Overall, students from Kentucky reported greater confidence in their 21st century skills (M=4.72) compared to students from Morgan State (M=4.19).

	Overall Sample (N=61)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=23)	
Efficacy – 21st Century Skills	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	4.39	.649	4.33	.739	4.72	.393	4.19	.648
I am confident I can lead others to accomplish a goal.	4.28	.804	4.33	.856	4.47	.800	4.09	.750
I am confident I can encourage others to do their best.	4.35	.777	4.33	.730	4.59	.795	4.18	.795
I am confident I can produce high quality work.	4.43	.673	4.33	.730	4.71	.470	4.32	.716
I am confident I can respect the differences of my peers.	4.48	.748	4.43	.870	4.88	.332	4.23	.752
I am confident I can help my peers.	4.47	.681	4.45	.759	4.81	.403	4.23	.685
I am confident I can include others' perspectives when making decisions.	4.43	.698	4.38	.805	4.76	.437	4.23	.685
I am confident I can make changes when things do not go as planned.	4.35	.732	4.33	.856	4.71	.470	4.09	.684
I am confident I can set my own learning goals.	4.34	.801	4.35	.745	4.65	.702	4.09	.868
I am confident I can manage my time wisely when working on my own.	4.32	.813	4.05	.921	4.71	.588	4.27	.767
When I have many assignments, I can choose which ones need to be done first.	4.40	.694	4.29	.845	4.76	.437	4.23	.612
I am confident I can work well with students from different backgrounds.	4.47	.700	4.48	.750	4.82	.393	4.18	.733
Scale (1=SD,2=D, 3=N, 4=A, 5=SA)								

Persistence

Students continued to indicate a strong intention to persist. More specifically, they indicated that they intended to earn their degree in their current major (M=4.57), planned to pursue an internship in the coming year (M=4.50), take courses in their major next year (M=4.48), continue their education in their major field (M=4.48) and get a job in their current discipline (M=4.45).

	Overall Sample (N=61)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=23)	
Intention to Persist	Mean	SD	Me an	SD	Mean	SD	Mean	SD
	4.07	.644	3.99	.676	4.28	.489	3.96	.702
Next year, I plan to take courses in my major discipline	4.48	.813	4.43	.978	4.76	.562	4.32	.780
I intend to get my degree in my current major	4.57	.722	4.67	.730	4.82	.393	4.27	.827
I am sure that I will continue my education in my major field	4.48	.701	4.43	.676	4.82	.393	4.27	.827
I intend to get an advanced degree in my major field	4.15	1.022	3.95	1.203	4.41	1.004	4.14	.834
I plan to pursue and secure an internship this year.	4.50	.701	4.43	.746	4.88	.332	4.27	.767
I intend to get a job in my major field	4.45	.811	4.52	.680	4.53	.874	4.32	.894
I can see myself working in my current field for at least 5 years.	4.37	.823	4.48	.750	4.41	.939	4.23	.813
I plan to devote my career to my current major discipline	4.14	1.042	4.14	1.062	4.18	1.185	4.10	.944
I plan to take additional courses related to machine learning.	3.88	1.091	3.71	1.271	4.24	.903	3.77	1.020
I intend to seek internship opportunities related to machine learning	4.00	.921	3.95	1.117	4.18	.728	3.91	.868
I am considering changing my major to something more directly related to machine learning	3.28	1.277	3.10	1.411	3.24	1.300	3.50	1.144
I plan to pursue an advanced degree related to machine learning	3.42	1.197	3.14	1.276	3.71	1.160	3.45	1.143
I plan to get a job related to machine learning.	3.55	1.11	3.48	1.123	3.71	1.105	3.50	1.144
I would like to have a career related to machine learning	3.62	1.09	3.52	1.123	4.06	.827	3.36	1.177
1=Not TRUE of me , 5=VERY TRUE of me								

Job Search and Career Preparation Skills

Career development was a unit within this course and students were engaged in activities aimed to better prepare them with the skills they need to get a job and begin their career. At the completion of the course, students indicated an increased level of confidence in their job search and career preparation skills. Students expressed the most confidence in their ability to receive and use feedback from others (M=4.13), preparing presentations (M=4.07), delivering strong oral presentations (M=3.95) and meeting and engaging with professionals in their field (M=3.95).

	Overall Sample (N=61)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=23)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	3.91	.747	3.95	.912	3.99	.602	3.82	.696
Constructing a resume	3.92	.809	4.10	.912	3.82	.728	3.83	.778
Meeting and engaging with professionals in your field	3.95	.902	4.05	.973	4.18	.636	3.70	.974
Giving feedback to others	3.95	.902	4.10	.944	4.00	.866	3.78	.902
Receiving and using feedback from others	4.13	.903	4.14	1.014	4.29	.772	4.00	.905
Working with recruiters or career services related to potential jobs	3.79	.897	3.81	1.030	3.76	.831	3.78	.850
Talking with faculty and others about potential internship of job opportunities	3.90	.851	3.76	.995	4.06	.827	3.91	.733
Preparing application materials for an internship or job	3.80	.833	3.81	.928	3.82	.809	3.78	.795
Preparing for a job interview	3.87	.922	3.90	1.044	3.82	.883	3.87	.869
Interviewing for an internship or job	3.85	.963	3.95	.973	3.94	.966	3.70	.974
Preparing for a presentation you will do	4.07	.873	4.10	.995	4.24	.664	3.91	.900
Delivering a strong oral presentation with confidence	3.95	.902	3.95	1.024	4.06	.748	3.87	.920
Learning about sources for potential internships or jobs	3.80	.853	3.76	.995	4.00	.707	3.70	.822
Applying for an internship or job opportunity	3.89	.968	3.90	1.091	3.94	1.029	3.83	.834
1=Not at all, 5=A great extent								

Career Readiness Competencies

Students continued to express and improve their confidence in their readiness for a career. Overall, students expressed confidence in their abilities, especially in terms of teamwork (M=4.34), technology (M=4.30), and equity and inclusion (M=4.23).

	Sample (N=61)		(n=21)		(n=17)		State (n=23)	
Career Readiness Competencies	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	4.18	.641	4.23	.733	4.32	.472	4.03	.654
Career and Self-Development - Awareness of strengths and weaknesses and seek relationships with professionals and opportunities to better prepare you for a career.	4.07	.854	4.00	.894	4.35	.702	3.91	.900
Communication - Able to clearly exchange information, ideas, facts, and perspectives wit people inside and outside of my current institution or organization.	4.10	.768	4.24	.831	4.06	.748	4.00	.739
Critical Thinking - Identify and respond to needs based upon an understanding of the context and a logical analysis of relevant information.	4.13	.826	4.29	.845	4.24	.752	3.91	.848
Equity and Inclusion - Demonstrate an awareness, attitude, knowledge, and skills required to equitably engage and include people from different cultures.	4.23	.783	4.33	.730	4.35	.786	4.04	.825
Leadership - Recognize and Capitalize on personal and team strengths to achieve organizational goals.	4.10	.831	4.19	.873	4.06	.748	4.04	.878
Professionalism - Knowing work environments differ greatly, understand and demonstrate effective work habits, and act in the interest of the larger community and workplace.	4.20	.813	4.10	1.044	4.47	.624	4.09	.668
Teamwork - Build and maintain collaborative relationships to work effectively toward common goals, while appreciating diverse viewpoints and share responsibilities.	4.34	.750	4.43	.676	4.53	.514	4.13	.920
Technology - Understand and leverage technology ethically to enhance efficiency, complete tasks and accomplish goals.	4.30	.760	4.29	.784	4.53	.624	4.13	.815
1-Not at all, 5=A great extent								

Career Interests

Finally, students expressed increase interest in jobs related to machine learning. Of the 10 careers listed below, students expressed the greatest interest in software engineering (M=3.81), software development (M=3.81), software programming (M=3.66) and artificial intelligence research (M=3.58).

	Overall Sample (N=61)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=23)	
Career Interests	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	3.50	.877	3.49	1.02	3.62	.711	3.41	.866
Software Engineer	3.81	1.224	3.81	1.504	4.00	1.095	3.68	1.041
Software Programmer	3.66	1.334	3.81	1.537	3.69	1.302	3.50	1.185
Software Developer	3.81	1.210	4.00	1.378	3.81	1.223	3.64	1.049
Data Scientist	3.41	1.271	3.25	1.552	3.69	1.078	3.36	1.136
Computer Engineer	3.50	1.188	3.67	1.278	3.13	1.302	3.59	1.008
Artificial Intelligence Research Scientist	3.58	1.086	3.67	1.155	3.62	1.088	3.45	1.057
Cloud Engineer	3.31	1.163	3.43	1.287	3.31	1.014	3.18	1.181
Machine Learning Scientist	3.36	1.200	3.14	1.389	3.88	.885	3.18	1.140
Machine Learning Engineer	3.44	1.222	3.24	1.446	3.88	.957	3.32	1.129
Big Data Engineer	3.12	1.326	3.10	1.586	3.06	1.181	3.18	1.220
1=Not at all interested, 5=Very interested								

Pre-Post Comparisons

A matched sample of 59 students was examined to determine the extent to which students changed (improved) from the beginning of the course to the end. The table below summarizes overall pre-post comparisons for 16 survey scales. Overall, improvements were observed on 14 of the 16 examined scales. The results of paired-samples t-tests are also reported. In order to control for Type 1 error, a Bonferroni correction was applied, resulting in an alpha level of .05/16 = .003. Using this corrected alpha level, statistical significance was found in relation to student confidence in their knowledge and skills required for the machine learning topics addressed in the course and the expected student learning outcomes. These effects (Cohen's d) also exceeded .80, resulting in large effect sizes.

		Pre		Post				
	N	Mean	SD	Mean	SD	t	p	Cohen's d
ML Topics Confidence	59	1.7369	.49536	3.2660	.91228	13.776	<.001	1.79
ML SLO Confidence	58	2.0080	.80426	3.6040	.93790	10.960	<.001	1.44
ABET SLO Confidence	59	3.7920	.85698	4.0248	.78110	2.046	.045	.266
ENG Efficacy – General Scale	59	4.1780	.69694	4.2367	.78278	.584	.562	.076
ENG Efficacy – Skills Scale	59	4.0237	.76211	4.2068	.81872	1.591	.117	.207
ENG Efficacy – Design Scale	59	3.7500	.88945	4.0441	.93297	2.136	.037	.278
ENG Efficacy – Tinkering Scale	59	3.6786	1.03304	3.8780	.93484	1.842	.071	.240
Longitudinal Assessment of Engineering Self-Efficacy	59	4.3257	.47308	4.2973	.56499	-.375	.709	-.049
21st Century Skills	58	4.4734	.54989	4.4018	.62985	-.808	.423	-.106
Persistence	58	4.0071	.57540	4.0453	.64301	.457	.649	.060
Career Development Unit Efficacy	58	3.7937	.74777	3.8912	.75190	.955	.343	.125
Career Readiness Confidence	57	4.1075	.73822	4.1974	.62943	1.185	.241	.157
ML Career Interest	55	3.4521	.90526	3.4723	.89509	.233	.817	.031
MSLQ – Critical Thinking	57	3.5895	.81890	3.8316	.71693	2.443	.018	.324
MSLQ – Self-Regulation	57	3.5637	.54014	3.6935	.65693	1.414	.163	.187
MSLQ – Peer Learning	56	3.4345	1.05585	3.8036	.82579	2.330	.023	1.19

Confidence in Knowledge and Skill – ML Topics

The table below summarizes overall pre-post comparisons for 39 topics from the applied Machine Learning course. Improvements were reported for all topics In order to control for Type 1 error, a Bonferroni correction was applied, resulting in an alpha level of .05/39 = .0013. Using this corrected alpha level, statistical significance was found in relation to 34 of the 39 topics summarized below. Of these 34 statistically significant improvements, 31 resulted in a large effect size.

		Pre		Post				
	N	Mean	SD	Mean	SD	t	p	Cohen's d
Computer Science	59	2.73	1.229	3.47	1.120	6.220	<.001	.810
Python	59	2.34	1.183	3.51	1.120	8.667	<.001	1.13
Straight Line Equation	58	2.74	1.596	3.41	1.377	3.108	.003	.408
Functions	58	3.31	1.217	3.71	1.185	2.653	.010	.348
Matrix Algebra	59	2.54	1.104	3.32	1.166	4.469	<.001	.582
Normal Distribution Properties	56	2.61	1.246	3.29	1.155	3.435	.001	.459
Hypothesis Testing	57	2.88	1.196	3.37	1.112	2.620	.011	.347
Probability and p-values	57	2.70	1.195	3.28	1.146	3.065	.003	.406
Data Science	57	1.84	1.049	3.26	1.009	8.765	<.001	1.16
Types of Machine Learning (ML) Models	58	1.31	.730	3.40	1.025	12.604	<.001	1.66
Ethical Consequences of Machine Learning	58	1.53	1.030	3.79	1.088	13.913	<.001	1.83
Data Analysis and Manipulation - Colab notebooks	59	1.37	.807	3.76	1.165	13.450	<.001	1.75
Data Analysis and Manipulation -Panda Series and Panda DataFrames	59	1.34	.779	3.76	1.150	13.745	<.001	1.79
Visualization of data	59	2.12	1.176	3.88	1.100	9.020	<.001	1.17
Acquiring and downloading data	58	2.31	1.273	3.84	1.152	7.393	<.001	.971
Exploratory data analysis	59	1.85	1.096	3.71	1.115	9.390	<.001	1.22
Regression analysis	59	1.80	1.047	3.49	1.104	9.432	<.001	1.23
Using scikit-learn for regression analysis	59	1.15	.407	3.39	1.232	14.223	<.001	1.85
Using TensorFlow	58	1.09	.283	3.28	1.089	15.626	<.001	2.05

(Continued on Page 56)

Confidence in Knowledge and Skill – ML Topics

(Continued from Page 55)

Binary Classification methods	59	1.44	.702	3.61	1.114	14.529	<.001	1.89
Multiclass Classification	56	1.30	.658	3.38	1.121	11.288	<.001	1.51
Image - Video Classification	59	1.44	.794	3.20	1.171	9.162	<.001	1.19
Deep Learning	58	1.57	1.061	3.19	1.131	8.665	<.001	1.14
Recurrent Neural Network	57	1.21	.526	3.14	1.109	12.875	<.001	1.71
Natural Language Processing	58	1.31	.598	3.02	1.017	12.668	<.001	1.66
Transfer Learning	57	1.32	.736	2.96	1.034	11.931	<.001	1.58
Clustering	58	1.45	.862	3.02	1.017	10.471	<.001	1.38
k-Means models	57	1.26	.583	3.07	1.015	12.875	<.001	1.71
Embedding	57	1.39	.881	3.00	1.086	9.639	<.001	1.28
Decision Trees and Random Forest	59	1.29	.617	3.15	1.014	12.772	<.001	1.66
Bayesian Modeling	59	1.12	.375	2.88	1.100	12.822	<.001	1.67
Support Vector Machines (SVM)	58	1.09	.283	2.81	1.083	12.632	<.001	1.66
XG Boost	59	1.07	.254	2.88	1.019	13.818	<.001	1.80
Activation Functions	59	1.20	.550	3.02	1.182	11.940	<.001	1.55
Big O	59	1.56	.952	2.69	1.087	7.045	<.001	.917
Dimensionality Reduction	59	1.14	.345	2.56	1.103	10.220	<.001	1.32
Loss Functions	58	1.22	.460	2.72	1.182	10.129	<.001	1.33
Probability and Statistics	58	2.62	1.211	3.17	1.187	3.167	.002	.416
Regular Expressions	59	2.22	1.378	3.03	1.129	3.953	<.001	.515

Confidence in ML Student Learning Outcomes

The table below summarizes overall pre-post comparisons for six student learning outcomes expected from the applied Machine Learning course. Improvements were reported for each SLO. Using a correct alpha level of .05/6 = .0083, all changes were statistically significant with 4 of the 6 reaching a large effect size.

		Pre		Post				
	N	Mean	SD	Mean	SD	t	p	Cohen's d
Investigate. clean and visualize data	56	2.75	1.352	3.89	1.073	4.940	<.001	.660
Understand and frame a problem as a supervised machine learning problem including whether it is a regression or classification problem and to incorporate the application requirements	58	1.72	1.022	3.53	1.030	9.884	<.001	1.29
Apply and tune common machine learning (ML) models in Python by making use of multiple ML toolkits	58	1.52	1.013	3.47	1.112	11.503	<.001	1.51
Demonstrate the ability to qualitatively and quantitatively evaluate the quality of trained regression and classification models	58	1.69	.995	3.47	1.047	10.641	<.001	1.39
Communicate technical concepts (oral and written) for an audience who may have limited technical background	58	2.71	1.389	3.67	1.176	5.069	<.001	.666
Identify the potential bias in ML models and explain its implications	58	1.71	.973	3.60	1.025	11.408	<.001	1.49

Changes Over Time by Site

University of Arkansas - A matched sample of 20 students from the University of Arkansas was examined to determine the extent to which students changed (improved) from the beginning of the course to the end. Overall, improvements were observed on 12 of the 16 examined scales. Using this corrected alpha level (.003), statistical significance was found in relation to student confidence in their knowledge and skills required for the machine learning topics addressed in the course and the expected student learning outcomes. These two effects also exceeded .80, resulting in large effect sizes.

University of Arkansas		Pre		Post				
	N	Mean	SD	Mean	SD	t	p	Cohen's d
ML Topics Confidence	20	1.8026	.55738	3.3391	1.17413	6.593	<.001	1.47
ML SLO Confidence	19	2.1386	.83454	3.6667	1.24722	4.849	<.001	1.11
ABET SLO Confidence	20	3.8455	.86047	4.0773	.98235	1.138	.269	.255
ENG Efficacy – General Scale	20	4.2167	.65583	4.2417	.92950	.110	.913	.025
ENG Efficacy – Skills Scale	20	3.8000	.93133	4.1800	.96660	1.520	.145	.340
ENG Efficacy – Design Scale	20	3.4800	.90937	3.9100	1.13039	1.397	.179	.312
ENG Efficacy – Tinkering Scale	20	3.4509	1.12748	3.7714	1.03329	1.551	.137	.347
Longitudinal Assessment of Engineering Self-Efficacy	20	4.4160	.44361	4.3696	.61431	-.372	.714	-.083
21st Century Skills	20	4.5409	.35818	4.3934	.69051	-1.076	.295	-.241
Persistence	20	4.0464	.53617	3.9464	.65255	-.879	.391	-.196
Career Development Unit Efficacy	20	3.8631	.77776	3.9462	.93551	.415	.683	.093
Career Readiness Confidence	19	4.2105	.71084	4.3158	.69643	.687	.501	.158
ML Career Interest	20	3.6100	.96295	3.4839	1.04682	-.967	.346	-.216
MSLQ – Critical Thinking	19	3.4526	.83757	3.7789	.89912	1.458	.162	.334
MSLQ – Self-Regulation	19	3.5263	.61241	3.6096	.78619	.410	.686	.094
MSLQ – Peer Learning	19	3.4211	1.24148	3.7719	1.00032	1.073	.297	.246

Changes Over Time by Site

University of Kentucky - A matched sample of 16 students from the University of Kentucky was examined to determine the extent to which students changed (improved) from the beginning of the course to the end. Overall, improvements were observed on all 16 examined scales. Using this corrected alpha level (.003), statistical significance was found in relation to student confidence in their knowledge and skills required for the machine learning topics, expected SLOs, ABET SLOs, Engineering Design and Tinkering efficacy, and Peer Learning. These effects also exceeded .80, resulting in large effect sizes.

University of Kentucky		Pre		Post				
	N	Mean	SD	Mean	SD	t	p	Cohen's d
ML Topics Confidence	16	1.5474	.36957	3.4423	.46339	12.600	<.001	3.15
ML SLO Confidence	16	1.5313	.55183	3.6583	.70737	9.518	<.001	2.38
ABET SLO Confidence	16	3.5568	.89065	4.3011	.54009	4.026	.001	1.01
ENG Efficacy – General Scale	16	3.9188	.74565	4.3000	.59876	3.015	.009	.754
ENG Efficacy – Skills Scale	16	3.9875	.70605	4.4125	.48700	3.232	.006	.808
ENG Efficacy – Design Scale	16	3.6156	.87211	4.3000	.66933	4.054	.001	1.01
ENG Efficacy – Tinkering Scale	16	3.4609	1.01522	4.0547	.91055	4.020	.001	1.01
Longitudinal Assessment of Engineering Self-Efficacy	16	4.2116	.48058	4.5082	.38847	2.772	.014	.693
21st Century Skills	16	4.3295	.68504	4.6977	.39900	2.515	.024	.629
Persistence	16	3.9777	.54941	4.2902	.50337	2.581	.021	.613
Career Development Unit Efficacy	16	3.6010	.68585	3.9327	.56098	2.072	.056	.518
Career Readiness Confidence	16	4.0993	.59347	4.2813	.45300	1.754	.100	.439
ML Career Interest	15	3.4030	.79959	3.6467	.72690	1.851	.085	.478
MSLQ – Critical Thinking	16	3.4625	.85391	3.9375	.72927	3.255	.005	.814
MSLQ – Self-Regulation	16	3.7064	.50207	4.0800	.58819	3.198	.006	.799
MSLQ – Peer Learning	15	3.4667	1.03740	4.2889	.78545	3.616	.003	.934

Changes Over Time by Site

Morgan State University - A matched sample of 23 students from the Morgan State University was examined to determine the extent to which students changed (improved) from the beginning of the course to the end. Overall, Morgan State students reported similar post-course responses when compared to their pre responses, increasing on 4 of the 16 summarized below, Using this corrected alpha level (.003), statistical significance was found in relation to student confidence in their knowledge and skills required for the machine learning topics addressed in the course and the expected student learning outcomes. These two differences also exceeded .80, resulting in large effect sizes.

Morgan State University	Pre			Post				
	N	Mean	SD	Mean	SD	t	p	Cohen's d
ML Topics Confidence	23	1.8115	.49964	3.0797	.89074	8.105	<.00	1.69
ML SLO Confidence	23	2.2319	.81609	3.5145	.80703	6.936	<.00 0	1.45
ABET SLO Confidence	23	3.9091	.83590	3.7870	.67751	-.754	.459	-.157
ENG Efficacy – General Scale	23	4.3246	.67624	4.1884	.78705	-1.034	.312	-.216
ENG Efficacy – Skills Scale	23	4.2435	.58762	4.0870	.86723	-.975	.340	-.203
ENG Efficacy – Design Scale	23	4.0783	.81294	3.9826	.90436	-.544	.592	-.113
ENG Efficacy – Tinkering Scale	23	4.0280	.89648	3.8478	.88465	-1.142	.266	-.238
Longitudinal Assessment of Engineering Self-Efficacy	23	4.3265	.49571	4.0879	.57432	-1.878	.074	- 392
21st Century Skills	22	4.5165	.58942	4.1942	.64788	-2.302	.032	-.491
Persistence	22	3.9928	.64854	3.9570	.70202	-.214	.833	-.046
Career Development Unit Efficacy	22	3.8709	.77155	3.8112	.71206	-.377	.710	-.080
Career Readiness Confidence	22	4.0244	.86698	4.0341	.66947	.077	.940	.016
ML Career Interest	20	3.3311	.94191	3.3300	.86396	-.007	.995	-.001
MSLQ – Critical Thinking	22	3.8000	.76842	3.8000	.53452	-.000	1.000	-.001
MSLQ – Self-Regulation	22	3.4921	.50431	3.4848	.45617	-.054	.957	-.012
MSLQ – Peer Learning	22	3.4242	.93821	3.5000	.50132	.326	.747	.070

Confidence in Knowledge and Skill – by Institution

The table summarizes overall pre-post comparisons for 39 topics from the applied Machine Learning course for each of the three sites. Improvements were reported for all topics In order to control for Type 1 error, a Bonferroni correction was applied, resulting in an alpha level of .05/39 = .0013. Using this corrected alpha level, statistical significance was found in relation to 34 of the 39 topics for the overall sample, 28 at Arkansas, 30 at Kentucky and 25 at Morgan State.

	Overall Sample		Arkansas		Kentucky		Morgan State	
ML Topics	N	Change[a]	N	Change	N	Change	N	Change
Computer Science	59	.746***	20	.650**	16	1.125***	23	.565*
Python	59	1.169***	20	1.250***	16	1.750***	23	.696**
Straight Line Equation	58	.672**	20	.350	15	.867	23	.826*
Functions	58	.397*	20	.100	16	.750*	22	.409
Matrix Algebra	59	.780***	20	.750*	16	.750	23	.826**
Normal Distribution Properties	56	.679**	19	.526	15	1.000*	22	.591
Hypothesis Testing	57	.491*	20	.550	15	.600	22	.364
Probability and p-values	57	.579**	20	.700*	15	.867	22	.273
Data Science	57	1.421***	19	1.474	16	2.188***	22	.818**
Types of Machine Learning (ML) Models	58	2.086***	20	2.050***	16	2.563***	22	1.773***
Ethical Consequences of Machine Learning	58	2.259***	20	2.100***	16	2.813***	22	2.000***
Data Analysis and Manipulation - Colab notebooks	59	2.390***	20	2.350***	16	3.188***	23	1.870***
Data Analysis and Manipulation -Panda Series and Panda DataFrames	59	2.424***	20	2.550***	16	3.000***	23	1.913***
Visualization of data	59	1.763***	20	1.700***	16	3.000***	23	.957**
Acquiring and downloading data	58	1.534***	19	1.526***	16	2.438***	23	.913**
Exploratory data analysis	59	1.864***	20	1.700***	16	2.750***	23	1.391***
Regression analysis	59	1.695***	20	1.800***	16	2.125***	23	1.304***
Using scikit-learn for regression analysis	59	2.237***	20	2.400***	16	2.500***	23	1.913***
Using TensorFlow	58	2.190***	19	2.263***	16	2.500***	23	1.913***
Binary Classification methods	59	2.169***	20	2.200***	16	2.563***	23	1.870***

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Confidence in Knowledge and Skill – by Institution

(Continued from Page 61)

Binary Classification methods	59	2.169***	20	2.200***	16	2.563***	23	1.870***
Multiclass Classification	56	2.071***	19	2.158***	14	2.714***	23	1.609***
Image - Video Classification	59	1.763***	20	1.900***	16	2.500***	23	1.130***
Deep Learning	58	1.621***	19	1.789***	16	2.313***	23	1.000**
Recurrent Neural Network	57	1.930***	19	2.053***	16	2.313***	22	1.545***
Natural Language Processing	58	1.707***	20	1.850***	16	2.063***	22	1.318***
Transfer Learning	57	1.649***	19	1.737***	16	2.063***	22	1.273***
Clustering	58	1.569***	19	1.842***	16	1.813***	23	1.174***
k-Means models	57	1.807***		1.842***	15	2.067***	23	1.609***
Embedding	57	1.614***	19	1.632***	16	1.750***	22	1.500***
Decision Trees and Random Forest	59	1.864***		1.600***	16	2.438***	23	1.696***
Bayesian Modeling	59	1.763***	20	1.650***	16	1.688***	23	1.913***
Support Vector Machines (SVM)	58	1.724***	20	1.750***	16	1.688***	22	1.727***
XG Boost	59	1.814***	20	1.800***	16	1.813***	23	1.826**
Activation Functions	59	1.814***	20	1.850***	16	2.000***	23	1.652***
Big O	59	1.136***	20	.750*	16	.938*	23	1.609***
Dimensionality Reduction	59	1.424***	20	1.500***	16	1.125***	23	1.565***
Loss Functions	58	1.500***	20	1.500***	15	1.533***	23	1.478***
Probability and Statistics	58	.552**	20	.900**	15	.467	23	.304
Regular Expressions	59	.814***	20	1.000**	16	1.125*	23	.435

a-Confidence scale (1=Not at all, 5= A great extent)
*p < .05, **p<.01,***p<.001

Confidence in ML Student Learning Outcomes by Institution

The table summarizes overall pre-post comparisons for six student learning outcomes expected from the applied Machine Learning course for each site. Improvements were reported for each SLO. Using a correct alpha level of .05/6 = .0083, all changes were statistically significant in the overall sample and at Kentucky with 5 of 6 at Morgan State and 4 of the 6 at Arkansas.

	Overall Sample		Arkansas		Kentucky		Morgan State	
	N	Change[a]	N	Change[a]	N	Change[a]	N	Change[a]
Investigate. clean and visualize data	56	1.143***	18	.611	15	2.067***	23	.957**[b]
Understand and frame a problem as a supervised machine learning problem including whether it is a regression or classification problem and to incorporate the application requirements	58	1.810***	19	1.684***	16	2.375***	23	1.522***
Apply and tune common machine learning (ML) models in Python by making use of multiple ML toolkits	58	1.948***	19	2.000***	16	2.438***	23	1.565***
Demonstrate the ability to qualitatively and quantitatively evaluate the quality of trained regression and classification models	58	1.776***	19	2.053***	16	2.250***	23	1.217***
Communicate technical concepts (oral and written) for an audience who may have limited technical background	58	.966***	19	.789*	16	1.563***	23	.696*
Identify the potential bias in ML models and explain its implications	58	1.897***	19	2.000***	16	2.000***	23	1.739***

a-Confidence scale (1=Not at all, 5= A great extent)
b-p=.006
*p < .05, **p<.01,***p<.001

Summary and Recommendations

Re-examine student prerequisites –
Students described challenges in learning programming and were limited in other background skills to do the work in a timely manner. They specifically indicated that having more experience with programming, statistics and linear Algebra would be beneficial. Faculty also expected that students with minimal programming knowledge would have difficulty. At the end of the course, one faculty member expressed concern for numerous students who were so behind after 3 weeks that they didn't benefit from the latter parts of the course and that the different levels of experience coming into AMLI was a significant challenge.

Allow for Curriculum Modification -
The existing curriculum serves as a guide but instructors may need to make modifications to better serve students. Two items, focused on student ability to keep up with the pace and have a good understanding what was addressed in class, received the lowest average daily favorable each week and were among the lowest 3 items on the weekly feedback. Student feedback and focus groups also indicated that more time and examples would be helpful. On the post survey, 3 of 4 faculty described the need to supplement the course curriculum with additional information, resources and examples for students and some topics required more time. Finally, students described having to frequently ask other students in the class or search online videos and resources to try and catch up and having more applied examples, resources, and more non-graded assignments with feedback would be very helpful.

Examine Course Organization Options -
Student focus group comments and ongoing feedback described challenges they had navigating through the course materials and assignments. They suggested using a learning management system (LMS) such as Canvas or Blackboard with which they are students are familiar. There are many built-in organizational features within these LMS such as a dashboard that alert participants (students, TAs and instructors) of the course schedule and when upcoming assignments are due. LMS also offer a way to organize course materials and storage for completed assignments that can be reviewed when preparing for subsequent tasks.

Provide Consistent Instructional approaches across sites–
Two sites had a face-to-face instructor every other day while the third site participated remotely each day. At the end of the course, faculty comments also described the challenges of using a hybrid approach. Instructional delivery options should be consistent across sites. While all sites generally provided very positive feedback related to the instructor's command of the content and the helpfulness of the teaching assistants, student focus groups and comments reflected the difference experiences. More specifically, students participating remotely described being less attentive and engaged with no instructor in their room and indicated that they would be more engaged if an instructor was present. Students from all sites expressed some challenges related to the technology (audio on mute, limited camera angles) making it more difficult to keep up with the class.

Follow-up Course Participants –
An attempt was made by the evaluator in Fall to follow up on course participants to determine the extent to which they were applying what they experienced in summer to be more confident in coursework, internship opportunities, job interviews and preparation for careers. This attempt did not yield a sufficient response. Program leaders should explore alternative methods to reach out to past participants so they can learn how the course is being applied and what aspects may require revision to better prepare future students.

Resources and References

Applied Machine Learning Course: Instructor Guide

ABET Student Learning Outcomes - https://www.abet.org/accreditation/accreditation-criteria/criteria-for-accrediting-engineering-programs-2018-2019/#GC3

DeChenne, S.E., Enochs, L.G. & Needham, M. (2012). Science, technology, engineering, and mathematics graduate teaching assistants teaching self-efficacy. Journal of Scholarship of Teaching and Learning, 12(4) 102-123.

LAESE – Longitudinal Assessment of Engineering Self-Efficacy - http://aweonline.org/efficacy.html

Mamaril, N.A., Usher. E. L., Li, C, R., Economy, D. R., & Kennedy, M. S. (2016). Measuring Undergraduate Students' Engineering Self-Efficacy: A Validation Study. Journal of Engineering Education, 105 (2), 366-395.

Midgley, C., Maehr, M. L., Hruda, L. Z., Anderman, E., Anderman, L., Freeman, K. E., Gheen, M., Kaplan, A., Kumar, R., Middleton, M. J., Nelson, J., Roeser, R., & Urdan, T., Manual for the Patterns of Adaptive Learning Scales (PALS), Ann Arbor, MI: University of Michigan, 2000

Pintrich, Paul R., and Elisabeth V. De Groot. (1990) Motivational and self-regulated learning components of classroom academic performance. Journal of Educational Psychology, 82 (1), 33-40.

Pintrich, P. R., Smith, D. A. F., Garcia, T., McKeachie, W. J. (1991). A manual for the use of the Motivated Strategies for Learning Questionnaire (MSLQ). Ann Arbor, MI: National Center for Research to Improve Postsecondary Teaching and Learning. ERIC Document 338122.

Pit Ho Patrio Chiu & Paul Corrigan | (2019) A study of graduate teaching assistants' self-efficacy in teaching: Fits and starts in the first triennium of teaching, Cogent Education, 6:1, 1579964, DOI: 10.1080/2331186X.2019.1579964

Unfried, A., Faber, M., Stanhope, D. & Wiebe, E. (2015). The development and validation of a measure of student attitudes toward science, technology, mathematics, and engineering. Journal of Psychoeducational Assessment. doi: 10.1177/0734282915571160

Yoon, S.Y., Evans, M. G., & Strobel, J. (2014). Validation of the Teaching Engineering Self-Efficacy Scale. Journal of Engineering Education, 103(3), 463-485.

Applied Machine Learning Course Evaluation

EVALUATION REPORT
SUMMER 2022

David M. Shannon, Auburn University

C.A.S.E. Academy

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Sample Characteristics

Sample - A pre-survey was administered to students enrolled in the Applied Machine Learning course during the first week of the course. A total of 62 students responded across the three institutions. The typical student identified as male (74.6%), African American (74.6%), non-Hispanic (73%) and without a disclosed disability (90.5%). Overall, nearly 60% of the students were of junior or senior status and 55.6% reported majoring in Engineering and over 40% expected to earn at least a Masters' degree.

Sample Characteristics	Overall Sample (N=62)	Arkansas (n=21)	Kentucky (n=17)	Morgan State (n=24)
Gender (Pronoun)				
He	47 (75.8%)	18 (85.7%)	13 (76.5%)	16 (66.7%)
She	12 (19.4%)	3 (14.3%)	2 (11.8%)	7 (29.2%)
They	1 (1.6%)	0	1 (5.9%)	0
Prefer not to answer	2 (3.2%)	0	1 (5.9%)	1 (4.2%)
Hispanic				
No	46 (74.2)	14 (66.7%)	10 (58.8%)	22 (91.7%)
Yes	15 (24.2%)	7 (33.3%)	7 (41.2%)	1 (4.2%)
Prefer not to answer/no response	1 (1.6%)			1 (4.2%)
Race[a]				
Am. Indian/Alaskan Native	3 (4.8%)	0	1 (5.9%)	2 (8.3%)
Asian or Pacific Islander	1 (1.6%)	1 (4.8%)	0	0
Black or African American	47 (75.8%)	12 (57.1%)	11 (64.7%)	24 (100%)
Native Hawaiian or Pacific Islander	0	0	0	0
White	12 (19.4%)	6 (26.6%)	5 (29.4%)	1 (4.2%)
Prefer not to anwer	2 (3.2%)	0	2 (11.8%)	0
Other	2 (3.2%)	2 (9.5%)	0	0
Disability				
No	57 (91.9%)	20 (95.2%)	15 (88.2%)	22 (91.7%)
Yes	1 (1.6%)	0	0	1 (4.2%)
Prefer not to answer	4 (6.4%)	1 (4.8%)	2 (11.8%)	1 (4.2%)
Academic Status				
FR	2 (3.2%)	1 (4.8%)	1 (5.9%)	0
SO	19 (30.6%)	7 (33.3%)	7 (41.2%)	5 (20.8%)
JR	26 (41.7%)	11 (52.4%)	4 (23.5%)	11 (45.8%)
SR	11 (17.7%)	2 (9.5%)	4 (23.5%)	5 (20.8%)
Other/no response	4 (6.4%)		1 (5.9%)	3 (12.5%)
Major				
Engineering	35 (58.5%)	12 (57.1%)	5 (29.4%)	18 (75%)
Computer Science	22 (35.5%)	8 (38.1%)	8 (47.1%)	6 (25%)
Data Science	2 (3.2%)	0	2 (11.8%)	
Physics	1 (1.6%)	0	0	
Mathematics	1 (1.6%)	0	1 (5.6%)	
Other	2 (3.2%)	1 (4.8%)	1 (5.6%)	

Faculty and Teaching Assistants

A total of 12 responses (Faculty =4, TAs=8) were recorded for the pre-instruction survey. The typical instructor (faculty and TA) identified as male, Asian, non-Hispanic and not disclosing a disability. There are a total of nine (9) responses on the post-course survey. The typical post-respondent identified as male, non-Hispanic, African American and not disclosing a disability. In addition, participants reported the number of days they were involved in the course

	Pre Course Survey			Post-Course Survey		
Sample Characteristics	Overall Sample (N=12)	Faculty (n=4)	TAs (n=8)	Overall Sample (N=9)	Faculty (n=4)	TAs (n=5)
Gender (Pronoun) **He** **She** **They** **Prefer not to answer**	 9(75%) 3(25%)	 3(75%) 1(25%)	 6(75%) 2(25%)	 5(55.6%) 2(22.2%) 1(11.1%) 1(11.1%)	 2 (50%) 1 (25%) 1 (25%) 0	 3 (60%) 1 (20%) 0 1 (20%)
Hispanic **No** **Yes** **Prefer not to answer**	 12 (100%) 0 0	 4 (100%) 0 0	 8 (100%) 0 0	 8(88.9%) 0 1(11.1%)	 4 (100%) 0 0	 4 (80%) 0 1 (20%)
Race **Am. Indian/Alaskan Native** **Asian or Pacific Islander** **Black or African American** **Nat Hawaiian or Pac Islander** **White** **Other** **Prefer not to answer**	 0 7 (58.3%) 4 (33.3%) 0 1 (8.3%) 0 0	 0 2 (50%) 1 (25%) 0 1 (25%) 0 0	 0 5 (62.5%) 3 (37.5%) 0 0 0 0	 0 3(33.3%) 4(44.4%) 0 2(22.2%) 0 0	 0 1 (25%) 2 (50%) 0 1 (25%) 0 0	 0 2 (40%) 2 (40%) 0 1 (20%) 0 0
Disability **No** **Yes** **Prefer not to answer**	 12 (100%)	 4. (100%)	 8 (100%)	 5(55.5%) 0 3(33.3%)	 2(75%) 0 1(25%)	 3(60%) 0 2(40%)
Participation -Number of Classes					M=5.5, SD=2.1, Range=3-8	M=31, SD=8.9, Range=20-40

Why did Students Enroll in the Course?

Students expect this Applied Machine Learning course to be valuable for a variety of reasons. In the overall sample, over 50% indicated that they thought they would learn something useful for their classes (60%), were curious to know more about machine learning (60%), just wanted to learn something new (60%), thought the course would be helpful in getting an internship (61%) and getting a job (66%).

	Overall Sample (N=62)	Arkansas (n=21)	Kentucky (n=17)	Morgan State (n=24)
	Percentage	Percentage	Percentage	Percentage
My advisor encouraged me	.42	.57	.24	.42
I like the applications of machine learning	.39	.43	.41	.33
I had nothing better to do with my time this summer	.18	.19	.18	.17
My peers were applying too	.11	.19	.00	.13
I was curious to know what the Machine Learning was about	.60	.57	.76	.50
I have done other summer programs and this one looked different	.08	.10	.06	.08
I thought I may learn something useful for my classes	.60	.62	.59	.58
Someone in my family encouraged me	.10	.10	.12	.08
I thought this would be helpful in getting me an internship	.61	.67	.59	.58
I thought this would be helpful in getting a job	.66	.57	.71	.71
I thought this would be helpful if/when applying to graduate degree programs	.35	.38	.35	.33
I was recruited at my school	.18	.10	.12	.29
I wanted to learn something new	.60	.76	.41	.58
I wanted to be around others that like the same things I do	.23	.33	.12	.21
I am interested in jobs related to machine learning	.48	.52	.59	.37
The course would help me figure out what I want to do in the future	.47	.43	.47	.50
I'm not sure	.00	.00	.00	.00

Pre and Post Survey Measurement Scales

Students

Several scales were constructed from survey items included in the pre and post survey administrations. These scales included the applied machine learning course objectives and student learning outcomes (SLOs), ABET SLOs, Engineering efficacy, persistence, career readiness and culturally responsive teaching. Overall, reliability estimates were very supportive, ranging from .831 to .965 on the pre administration and from .886 to .983 at post.

		Students		
Scale	**Items**	**Pre**	**Post**	**Description**
Applied ML Course Units/Topics	39	.965	.977	Confidence in knowledge and ability related to each topic in the course.
Applied ML SLOs	6	.891	.886	Confidence in knowledge and abilities related to student learning outcomes
Career Development Units	13	.957	.965	Confidence in knowledge and ability related to career development topics.
Career Readiness	8	.931	.926	Competencies for Career Readiness – National Association Of Colleges and Employers
Interest in ML Careers/Jobs	10	.853	.909	Interest in ML-related jobs/careers
ABET SLOs	11	.937	.940	Confidence in the knowledge and ability related to the ABET SLOs
Engineering Efficacy				Undergraduate Students' Engineering Self-Efficacy
General Knowledge and Ability	6	.881	.937	
Engineering Skills	5	.830	.893	
Engineering design	5	.939	.943	
Tinkering Skills	8	.935	.944	
Intent to Persist	14	.875	.893	Persistence in degree and career
Longitudinal Assessment of Engineering Efficacy	23	.935	X	Longitudinal Assessment of Engineering Self-Efficacy
21st Century Skills	11	.943	X	Confidence in relation to 21st century skills (e.g. teamwork, communication)
Culturally Responsive Teaching Self Efficacy	27	X	.983	Students' perceptions of instructors' use of culturally responsive teaching approaches
Culturally Responsive Teaching Outcome Expectations Scale	20	X	.954	Students perceptions of outcomes expected from culturally responsive teaching

Pre Course Survey Findings

Confidence in Machine Learning Student Learning Outcomes

As might be expected, students were not generally very confident in their knowledge and abilities related to the Applied Machine Learning Course student learning outcomes prior to course instruction. Overall, they indicated the greatest confidence in their ability to investigate, clean and visualize data and least confidence in their ability to apply and tune machine learning models, identify the potential bias in ML models and evaluate the quality of trained regression and classification models.

	Overall Sample (N=62)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=24)	
ML Course SLO	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Investigate. clean and visualize data	2.85	1.289	3.19	1.504	3.24	1.091	2.26	1.010
Understand and frame a problem as a supervised machine learning problem including whether it is a regression or classification problem and to incorporate the application requirements	2.02	1.162	2.24	1.338	2.13	1.088	1.75	1.032
Apply and tune common machine learning (ML) models in Python by making use of multiple ML toolkits	1.75	1.043	1.86	1.153	1.75	1.125	1.67	.917
Demonstrate the ability to qualitatively and quantitatively evaluate the quality of trained regression and classification models	1.97	1.080	2.14	1.276	2.00	1.155	1.79	.833
Communicate technical concepts (oral and written) for an audience who may have limited technical background	2.70	1.308	2.81	1.537	2.56	1.315	2.71	1.122
Identify the potential bias in ML models and explain its implications	1.87	.991	1.95	1.024	1.94	1.124	1.75	.897
Scale (1=Not at all, 5=A great extent)								

Confidence in ABET Student Learning Outcomes

At the beginning of the course, students did express a moderately high level of confidence in the knowledge and ability related to the ABET student learning outcomes as all responses averaged above the scale midpoint of 3 and 8 of the 11 averaging 3.5 or above. Students were especially confident in their ability to communicate effectively (M=4.11), understand their professional and ethical responsibilities (M=3.97), recognize the need and ability to engage in professional development/improvement (M=3.87) and work effectively on multidisciplinary teams (M=3.89).

	Overall Sample (N=62)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=24)	
ABET SLO	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Apply knowledge of mathematics, science and engineering	3.67	1.012	3.90	.889	3.56	1.209	3.54	.977
Design and conduct experiments and interpret the resulting data	3.48	1.170	3.81	1.078	3.29	1.312	3.33	1.129
Design a system, component, or process to meet desired needs	3.41	1.160	3.57	1.207	3.50	1.265	3.21	1.062
Work effectively on a multidisciplinary team	3.92	1.076	4.19	1.123	3.71	1.105	3.83	1.007
Identify, formulate and solve engineering problems	3.43	1.024	3.52	1.209	3.25	1.183	3.46	.721
Understand professional and ethical responsibility	4.00	1.033	4.10	1.300	4.00	.894	3.92	.881
Communicate effectively	4.15	.899	4.15	1.040	3.87	.719	4.33	.868
Understand the broad impact of engineering solutions in a global, economic, environmental and social context	3.65	1.073	3.76	1.091	3.24	1.147	3.83	.963
Recognize the need for and ability to engage in professional development/ improvement	3.89	.994	4.00	1.095	3.82	1.015	3.83	.917
Understanding and awareness of contemporary issues	3.66	.974	3.71	1.007	3.71	.920	3.58	1.018
Ability to use the techniques, skills, and modern engineering tools necessary for engineering practice.	3.61	1.014	3.81	.981	3.35	1.115	3.62	.970
Scale (1=Not at all, 5=A great extent)								

Confidence in Machine Learning Units and Topics

Confidence in Machine Learning Student Learning Outcomes

Students were asked to indicate the extent to which they confident in their knowledge and ability related to each of the units and topics to be addressed in the Applied Machine Learning Course. Consistent with their confidence in the overall student learning outcomes, students were not very confident in their knowledge and abilities related to the specific content in the course prior to course instruction. These will be examined again at the end of the course to determine improvement in their confidence

	Overall Sample (N=62)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=24)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Computer Science	3.05	1.146	3.10	1.294	3.29	.772	2.83	1.239
Python	2.66	1.187	2.19	1.030	3.12	1.054	2.75	1.294
Straight Line Equation	3.05	1.465	3.14	1.424	3.38	1.668	2.75	1.359
Functions	3.68	1.128	4.14	.727	3.71	1.312	3.25	1.152
Matrix Algebra	2.72	1.213	2.76	1.338	3.35	1.057	2.22	.998
Normal Distribution Properties	2.85	1.278	3.10	1.261	2.76	1.300	2.71	1.301
Hypothesis Testing	3.07	1.289	3.52	1.327	3.12	1.166	2.61	1.234
Probability and p-values	2.87	1.282	3.38	1.117	2.69	1.352	2.52	1.275
Data Science	2.34	1.031	2.62	1.071	2.24	1.147	2.17	.887
Types of Machine Learning (ML) Models	1.75	.925	1.90	1.221	1.62	.719	1.71	.751
Ethical Consequences of Machine Learning	2.12	1.223	2.40	1.392	2.12	1.360	1.87	.947
Data Analysis and Manipulation - Colab notebooks	1.92	1.085	1.81	1.078	2.00	1.155	1.96	1.083
Data Analysis and Manipulation -Panda Series and Panda DataFrames	1.74	1.047	1.76	1.091	1.75	1.125	1.71	.999
Visualization of data	2.71	1.200	2.89	1.329	3.00	1.461	2.35	.775
Acquiring and downloading data	2.85	1.233	2.95	1.322	3.00	1.366	2.65	1.071
Exploratory data analysis	2.30	1.101	2.33	1.155	2.50	1.211	2.13	.992
Regression analysis	2.15	1.223	2.43	1.326	2.37	1.360	1.75	.944
Using scikit-learn for regression analysis	1.65	.971	1.65	1.137	1.69	.946	1.63	.875
Using TensorFlow	1.46	.828	1.57	1.076	1.38	.619	1.42	.717
Binary Classification methods	1.85	1.087	2.00	1.338	1.69	.946	1.83	.963
Multiclass Classification	1.80	1.147	1.95	1.395	1.75	1.125	1.71	.955
Image - Video Classification	1.68	.990	1.89	1.286	1.44	.892	1.67	.761

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Confidence in Machine Learning Units and Topics

(Continued from Page 9)

Deep Learning	1.83	1.122	2.10	1.252	1.50	1.033	1.83	1.049
Recurrent Neural Network	1.56	.958	1.86	1.276	1.31	.602	1.46	.779
Natural Language Processing	1.77	1.079	1.85	1.268	1.69	1.195	1.75	.847
Transfer Learning	1.53	.929	1.75	1.118	1.44	1.031	1.42	.654
Clustering	1.80	1.108	1.95	1.203	1.88	1.310	1.62	.875
k-Means models	1.68	.983	1.80	1.105	1.81	1.167	1.50	.722
Embedding	1.81	1.131	1.90	1.136	1.81	1.276	1.71	1.056
Decision Trees and Random Forest	1.78	1.075	2.05	1.359	1.88	1.025	1.48	.730
Bayesian Modeling	1.57	1.047	1.95	1.465	1.44	.727	1.30	.635
Support Vector Machines (SVM)	1.41	.824	1.57	1.076	1.31	.793	1.33	.565
XG Boost	1.32	.748	1.55	1.099	1.13	.342	1.25	.532
Activation Functions	1.52	.942	1.67	1.017	1.56	1.209	1.38	.647
Big O	2.13	1.346	2.24	1.546	2.53	1.356	1.79	1.103
Dimensionality Reduction	1.48	.887	1.67	1.111	1.50	.966	1.29	.550
Loss Functions	1.58	1.021	1.70	1.218	1.60	1.121	1.46	.779
Probability and Statistics	3.00	1.329	3.38	1.396	3.06	1.289	2.63	1.245
Regular Expressions	2.77	1.270	3.00	1.483	2.69	1.250	2.63	1.096
Scale (1=Not at all, 5= A great extent)								

Engineering Self-Efficacy

In general, students indicated moderately high levels of confidence related to engineering with all items averaging above the scale mid-point of 3. At the beginning of this course, students were especially confident in relation to general efficacy and skills efficacy.

	Overall Sample (N=62)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=24)	
Engineering Self-Efficacy	Mean	SD	Mean	SD	Mean	SD	Mean	SD
General Self-Efficacy	4.19	.61	4.31	.54	4.22	.56	4.07	.71
I can master the content in my major courses	4.25	.722	4.33	.577	4.56	.629	3.96	.806
I can master the content in even the most challenging engineering course	3.77	.895	4.00	.775	3.94	.827	3.46	.977
I can do good work in my major coursework	4.35	.812	4.52	.680	4.41	.618	4.17	1.007
I can do an excellent job on engineering-related problems or tasks I am assigned	4.18	.736	4.33	.577	3.94	.748	4.21	.833
I can learn the content taught in my engineering-related courses	4.37	.683	4.38	.740	4.35	.606	4.37	.711
I can earn good grades in my engineering-related courses	4.27	.772	4.33	.658	4.24	.752	4.25	.897
Engineering Skills Self-Efficacy	4.14	.61	4.23	.61	4.10	.72	4.09	.72
I can perform experiments independently	3.84	.978	4.19	.873	3.59	1.004	3.71	.999
I can analyze data from experiments	4.15	.807	4.29	.644	4.18	.728	4.00	.978
I can orally communicate results from experiments	4.18	.820	4.24	.700	4.00	.866	4.25	.897
I can communicate results in written form	4.26	.788	4.10	.831	4.35	.702	4.33	.816
I can solve problems using a computer	4.29	.797	4.33	.796	4.41	.618	4.17	.917
Design Self-Efficacy	3.89	.76	4.01	.65	3.86	.75	3.81	.86
I can design new things	4.00	.887	4.19	.750	3.82	.951	3.96	.955
I can identify a design need	3.82	.840	3.90	.768	3.88	.857	3.71	.908
I can develop design solutions	3.94	.807	4.10	.700	3.88	.857	3.83	.868
I can evaluate a design	3.89	.851	4.05	.669	3.82	.951	3.79	.932

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Engineering Self-Efficacy

(Continued from Page 11)

I can reorganize changes needed for a design solution to work	3.81	.884	3.86	.854	3.82	.728	3.75	1.032
Tinkering Self-Efficacy	3.81	.89	3.97	.69	3.44	.98	3.93	.92
I can work with tools and use them to build things	3.90	1.003	4.10	.889	3.41	1.004	4.08	1.018
I can work with tools and use them to fix things	3.95	.931	4.14	.854	3.53	1.007	4.08	.881
I can work with machines	3.90	1.127	4.29	.956	3.41	1.176	3.92	1.139
I can fix machines	3.24	1.155	3.38	.973	3.00	1.369	3.29	1.160
I can manipulate components and devices	3.67	.961	3.80	.834	3.35	1.115	3.79	.932
I can assemble things	4.00	.992	4.05	.669	3.65	1.169	4.21	1.062
I can disassemble things	3.97	1.086	4.10	.831	3.53	1.328	4.17	1.049
I can apply technical concepts in engineering	3.87	1.032	4.05	.805	3.41	1.278	4.04	.955
Scale (1=SD,2=D, 3=N, 4=A, 5=SA)								

Longitudinal Assessment of Engineering Self-Efficacy

Students expressed high levels of efficacy in response to the LAESE items with responses averaging above 3.5 and all but 6 above 4.0. Students most strongly agreed that they able to make friends with people with different backgrounds (M=4.65) and values and they would complete their degree at their current institution (M=4.61).

	Overall Sample (N=62)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=24)	
LAESE Items	Mean	SD	Mean	SD	Mean	SD	Mean	SD
I can relate to people around me in my classes	3.98	.975	3.71	1.007	3.88	1.088	4.29	.806
I can succeed in an engineering degree program	4.48	.646	4.57	.598	4.41	.712	4.46	.658
I have a lot in common with other students in my classes	3.84	.853	3.67	.856	3.76	.970	4.04	.751
Someone like me can succeed in an engineering career	4.43	.767	4.57	.598	4.19	1.109	4.48	.593
The other students in my classes share my personal interests	3.80	.853	3.76	.995	3.62	.885	3.96	.690
I can succeed in an engineering program while NOT having to give up participation in my outside interests (e.g. family, friends, extracurricular activities)	3.74	1.085	3.86	.964	3.71	1.105	3.67	1.204
I can relate to people around me in my extracurricular activities	4.06	.827	4.00	.707	3.76	1.147	4.33	.565
I can complete the math requirements for my degree program,	4.45	.761	4.43	.676	4.35	1.057	4.54	.588
Doing well in math will enhance my career/job opportunities	4.29	.982	4.19	.750	4.35	1.057	4.33	1.129
A degree in engineering will allow me to obtain a well paying job	4.52	.805	4.52	.680	4.29	1.105	4.67	.637
I will do well in my major courses this year	4.58	.615	4.48	.680	4.59	.618	4.67	.565

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Longitudinal Assessment of Engineering Self-Efficacy

(Continued from Page 13)

I will complete my degree at my current institution	4.61	.686	4.52	.680	4.53	.874	4.75	.532
A degree in engineering will give me the kind of lifestyle I want	4.47	.804	4.43	.676	4.24	1.091	4.67	.637
I can make friends with people from different backgrounds and/or values	4.65	.575	4.57	.598	4.59	.618	4.75	.532
Doing well in my classes will increase my sense of self-worth	4.31	.822	4.24	.768	4.12	.857	4.50	.834
I will feel "part of the group" on my job if I enter engineering	3.84	1.027	3.81	.873	3.47	1.125	4.13	1.035
I can complete the science (e.g. physics, chemistry) requirements for my degree	4.52	.741	4.52	.680	4.41	.939	4.58	.654
Taking advance math courses will help keep my career options option	3.95	1.137	3.95	1.024	3.88	1.166	4.00	1.251
A degree in engineering will allow me to get a job where I can use my talents and creativity	4.21	.926	4.14	.910	4.00	1.118	4.42	.776
I can persist in engineering this academic year.	4.46	.673	4.33	.730	4.47	.624	4.57	.662
I can approach a faculty or staff member to get assistance when needed.	4.13	.806	4.05	.759	4.12	.928	4.21	.779
I can adjust to new work or learning environments	4.47	.620	4.48	.602	4.47	.624	4.46	.658
A degree in engineering will allow me to get a job I like	4.41	.804	4.48	.602	4.06	1.088	4.61	.656
Scale (1=SD,2=D, 3=N, 4=A, 5=SA)								

Confidence in 21st Century Skills

Students expressed high levels of confidence in their ability in their 21st century skills, especially regarding their respect for the differences of their peers (M=4.65, their confidence in working with students from different backgrounds (M-4.58), include others' perspectives when making decisions (M=4.50).

	Overall Sample (N=62)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=24)	
Efficacy - 21st Century Skills	Mean	SD	Mean	SD	Mean	SD	Mean	SD
I am confident I can lead others to accomplish a goal.	4.18	.820	4.14	.793	4.00	1.00 0	4.33	.702
I am confident I can encourage others to do their best.	4.31	.841	4.19	.928	4.18	1.01 5	4.50	.590
I am confident I can produce high quality work.	4.50	.647	4.43	.676	4.53	.717	4.54	.588
I am confident I can respect the differences of my peers.	4.65	.575	4.48	.680	4.59	.507	4.83	.482
I am confident I can help my peers.	4.24	.824	4.10	.768	4.29	.849	4.33	.868
I am confident I can include others' perspectives when making decisions.	4.50	.741	4.38	.921	4.53	.624	4.58	.654
I am confident I can make changes when things do not go as planned.	4.44	.692	4.33	.796	4.35	.702	4.58	.584
I am confident I can set my own learning goals.	4.29	.857	4.10	.889	4.24	.903	4.50	.780
I am confident I can manage my time wisely when working on my own.	4.15	.938	4.10	.889	4.24	.831	4.13	1.076
When I have many assignments, I can choose which ones need to be done first.	4.40	.799	4.38	.921	4.41	.712	4.42	.776
I am confident I can work well with students from different backgrounds.	4.58	.691	4.38	.805	4.53	.717	4.79	.509

Persistence

Students generally indicated a strong intention to persist. More specifically, they indicated that they planned to take courses in their major next year (M=4.52), complete their current degree (M=4.55), continue their education in their current field (M=4.57) and see themselves working in the field for at least 5 years (M=4.52).

	Overall Sample (N=62)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=24)	
Intention to Persist	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Next year, I plan to take courses in my major discipline	4.52	.770	4.38	.805	4.47	.800	4.68	.716
I intend to get my degree in my current major	4.55	.746	4.48	.750	4.53	.717	4.64	.790
I am sure that I will continue my education in my major field	4.57	.698	4.48	.750	4.35	.702	4.82	.588
I intend to get an advanced degree in my major field	4.05	.910	4.05	.805	3.76	1.033	4.27	.883
I plan to pursue and secure an internship this year.	4.33	.851	4.29	.784	4.18	.951	4.48	.846
I intend to get a job in my major field	4.44	.827	4.48	.750	4.12	.993	4.65	.714
I can see myself working in my current field for at least 5 years.	4.52	.725	4.33	.796	4.47	.717	4.73	.631
I plan to devote my career to my current major discipline	4.44	.764	4.33	.796	4.29	.849	4.65	.647
I plan to take additional courses related to machine learning.	3.92	1.053	3.86	.964	4.06	1.197	3.87	1.058
I intend to seek internship opportunities related to machine learning	3.90	1.044	4.00	.894	3.88	1.111	3.83	1.154
I am considering changing my major to something more directly related to machine learning	2.92	1.094	3.30	1.081	2.76	1.091	2.70	1.063
I plan to pursue an advanced degree related to machine learning	3.23	1.146	3.48	1.078	3.59	1.064	2.74	1.137
I plan to get a job related to machine learning.	3.52	1.074	3.48	1.167	3.82	1.074	3.35	.982
I would like to have a career related to machine learning	3.54	.993	3.71	.956	3.71	1.047	3.26	.964
1=Not TRUE of me , 5=VERY TRUE of me								

Confidence in Career Development and Preparation

In general, students expressed confidence in their abilities as they prepare for a career with all but one item averaging above the scale midpoint. They indicated the greatest confidence in their abilities related their cultural awareness (M=4.33), teamwork skills (M=4.27), having high ethical standards (M=4.25 Areas in which there is room for improvement included security knowledge (M=3.31) and knowledge of physical science and engineering fundamentals (M=3.53).

Confidence in Career Development	Overall Sample (N=62)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=24)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Good communication skills	3.98	.965	4.05	1.024	3.76	.970	4.09	.921
Knowledge of physical science and engineering fundamentals	3.53	.833	3.71	1.056	3.41	.507	3.45	.800
Ability to identify, formulate, and solve engineering problems	3.71	.955	4.00	.858	3.50	1.033	3.59	.959
Curiosity and persistent desire for continuous learning	4.15	.880	4.29	.845	4.06	.966	4.09	.868
Self-drive and motivation	4.22	.904	4.24	.831	4.24	.903	4.18	1.006
Cultural awareness in the broad sense (nationality, ethnicity, gender, sexual orientation(	4.33	.877	4.48	.814	3.94	.899	4.50	.859
Ability to make good economic and business judgements and decisions	3.88	1.091	4.14	.910	3.35	1.057	4.05	1.174
High ethical standards	4.25	.856	4.38	.865	4.12	.697	4.23	.973
Critical thinking skills	4.17	.886	4.38	.805	3.94	.827	4.14	.990
Willingness to task calculated risks	3.92	.944	4.24	.831	3.59	.939	3.86	.990
Ability to prioritize efficiently	4.02	.854	4.19	.814	3.94	.659	3.91	1.019
Project management	3.68	1.074	3.90	1.044	3.65	.996	3.48	1.167
Teamwork skills	4.27	.800	4.33	.796	4.00	.707	4.41	.854
Entrepreneurship and intrapreneurship	3.62	1.121	3.95	1.024	3.50	1.155	3.38	1.161
Ability to use new technology	4.15	.860	4.24	.831	4.06	.748	4.14	.990
Applied knowledge of engineering core sciences	3.67	.962	3.86	.854	3.38	1.147	3.71	.902
Data interpretation and visualization skills	3.83	.968	4.05	.805	3.94	.854	3.55	1.143
Security knowledge (data, cyber, etc.)	3.31	1.249	3.95	.865	2.94	1.389	2.95	1.253
Leadership skills	3.98	1.033	4.05	.973	3.53	1.179	4.27	.883
Creativity	4.02	.982	4.20	.894	3.69	1.138	4.09	.921
Emotional intelligence	4.13	.833	4.19	.873	4.06	.827	4.14	.834
Research and evaluation skills	4.00	.939	4.14	.854	4.00	.935	3.86	1.037
1-not very confident, 5=very confident								

(Continued on Page 18)

Job Search and Career Preparation Skills

Career development is a unit with this course and students will be engaged in activities aimed to better prepare them with the skills they need to get a job and begin their career. In response to these items, students indicated a high level of confidence with all items averaging above 3.5 (using a 5-point scale). Students expressed the most confidence in their ability to receive and use feedback from others (M=4.26), prepare application materials for an internship of job (M=3.98), talk with faculty and others about potential internship or job opportunities (M=4.03), and apply for internship or job opportunities (M=4.07).

	Overall Sample (N=62)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=24)	
	Mean	SD	Mean	SD	Mean	SD	Mea n	SD
Constructing a resume	3.85	.910	3.95	.826	3.76	1.091	3.83	.868
Meeting and engaging with professionals in your field	3.92	1.021	4.15	.813	3.47	1.375	4.04	.806
Giving feedback to others	3.88	.885	4.05	.705	3.65	1.115	3.92	.830
Receiving and using feedback from others	4.26	.814	4.20	.768	4.18	.951	4.38	.770
Working with recruiters or career services related to potential jobs	3.93	.910	4.05	.826	3.59	1.121	4.08	.776
Talking with faculty and others about potential internship of job opportunities	4.03	.920	4.05	.826	3.88	1.088	4.13	.900
Preparing application materials for an internship or job	3.98	.846	4.10	.718	3.82	1.015	4.00	.834
Preparing for a job interview	3.74	.911	3.85	.745	3.53	1.068	3.79	.932
Interviewing for an internship or job	3.69	1.088	3.95	.887	3.35	1.320	3.71	1.042
Preparing for a presentation you will do	3.95	.865	4.05	.686	3.59	.939	4.12	.900
Delivering a strong oral presentation with confidence	3.80	1.030	3.95	.759	3.41	1.228	3.96	1.042
Learning about sources for potential internships or jobs	3.88	.885	4.10	.718	3.71	1.105	3.83	.834
Applying for an internship or job opportunity	4.07	.946	4.10	.788	3.82	1.185	4.21	.884
1=Not at all, 5=A great extent								

Career Readiness Competencies

Students were asked to indicate their confidence in relation to the eight competencies of career readiness in the table below. Overall, students expressed confidence in their abilities, especially in terms of teamwork (M=4.30), equity and inclusion (M=4.30) and professionalism (M=4.26).

	Overall Sample (N=62)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=24)	
Career Readiness Competencies	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Career and Self-Development - Awareness of strengths and weaknesses and seek relationships with professionals and opportunities to better prepare you for a career.	3.90	.936	3.95	.805	3.65	1.115	4.04	.908
Communication - Able to clearly exchange information, ideas, facts, and perspectives wit people inside and outside of my current institution or organization.	3.92	.893	4.14	.793	3.65	1.115	3.92	.776
Critical Thinking - Identify and respond to needs based upon an understanding of the context and a logical analysis of relevant information.	4.03	.809	4.19	.750	3.76	.970	4.08	.717
Equity and Inclusion - Demonstrate an awareness, attitude, knowledge, and skills required to equitably engage and include people from different cultures.	4.30	.782	4.35	.813	4.00	.866	4.46	.658
Leadership - Recognize and Capitalize on personal and team strengths to achieve organizational goals.	3.95	.884	4.05	.865	3.47	.943	4.22	.736
Professionalism - Knowing work environments differ greatly, understand and demonstrate effective work habits, and act in the interest of the larger community and workplace.	4.26	.788	4.19	.750	4.06	.899	4.46	.721
Teamwork - Build and maintain collaborative relationships to work effectively toward common goals, while appreciating diverse viewpoints and share responsibilities.	4.30	.803	4.19	.750	4.00	.935	4.61	.656
Technology - Understand and leverage technology ethically to enhance efficiency, complete tasks and accomplish goals.	4.18	.806	4.14	.793	4.12	.928	4.26	.752
1-Not at all, 5=A great extent								

Career Interests

Finally, students were asked to indicate their interest in specific careers related to machine learning. Of the 10 careers listed below, students expressed the greatest interest in software engineering (M=3.71), software development (M=3.64), software programming (M=3.64) and machine learning engineering (M=3.62).

	Overall Sample (N=62)		Arkansas (n=21)		Kentucky (n=17)		Morgan State (n=24)	
Career Interests	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Software Engineer	3.71	1.136	4.00	.837	3.76	1.200	3.42	1.283
Software Programmer	3.64	1.252	4.05	.826	3.65	1.272	3.29	1.459
Software Developer	3.64	1.265	3.95	.805	3.75	1.342	3.29	1.488
Data Scientist	3.15	1.226	3.48	1.078	3.41	1.278	2.67	1.204
Computer Engineer	3.39	1.178	3.48	.928	3.41	1.326	3.29	1.301
Artificial Intelligence Research Scientist	3.42	1.209	3.62	1.161	4.00	.935	2.83	1.204
Cloud Engineer	3.40	.995	3.76	.889	3.41	1.064	3.05	.950
Machine Learning Scientist	3.45	1.082	3.81	.814	3.35	1.169	3.21	1.179
Machine Learning Engineer	3.62	1.083	4.10	.912	3.41	1.121	3.38	1.096
Big Data Engineer	3.15	.989	3.52	.750	2.94	1.029	2.96	1.083
1=Not at all interested, 5=Very interested								

Please Describe the Career in Which you Intend to Pursue.

A total of 52 participants described their career plans. These responses are sorted into the primary categories summarized in the table below. These responses represented various fields with the most frequent being software engineering (15.4%), software development (13.5%), data science (13.5%), electrical engineering (11.5%) or other engineering specializations (13.5%).

Career Category	N (%)	Sample responses
Software Engineering	8 (15.4%)	-software engineer -Intend to pursue software engineering undecided. leaning towards software engineer -I intend to pursue a job in computer science, preferably software engineering.
Software Development	7 (13.5%)	- Software Development - I intend to be a software developer after working in IT for a few years and getting my certifications to put me on the path. - the creation of machine learning software
Data Science/AI	7 (13.5%)	-Data Scientist -I wish to pursue Artificial Intelligence, with a specific lean toward machine learning. - Develop efficient programs and data science solutions to help companies
Electrical Engineering	6 (11.5%)	-Electrical Engineer -I intend to have an electrical engineering career at any corporation that hires me. -Any form of industry-based job related to electrical or computer engineering
Computer Programming/ Engineering	4 (7.7%)	- A career that deals with some form of coding or programming. Also, a career with a hands on aspect like constructing circuits or devices. -I wish to become an computer engineer and work in the field of smart housing and the IoT
Robotics	3 (5.8%)	-the field of manufacturing and robotic engineering. -Autonomous robotics
Cybersecurity	3 (5.8%)	- Cyber security
Other Engineering fields	7 (13.5%)	Architectural engineering, Applied Engineering, civil engineering, Chemical Engineer
Other careers	3 (5.8%)	-I intend to work in a construction management position. -I am very interested into Fintech -FBI, CIA, or another government entity.
Undecided	4 (7.7%)	

Post Course Results

What did students gain from the course?

Students identified many ways in which the course benefitted them. In the overall sample, over 90% indicated that they learned applications of machine learning (95%), gained valuable knowledge related to machine learning (94%), and networked with other students in their discipline (92%). In addition, over 80% of students indicated gaining experience that would be useful for an internship of job.

	Overall Sample (N=62)	Arkansas (n=20)	Kentucky (n=19)	Morgan State (n=23)
	%	%	%	%
I learned about the applications of machine learning	95	100	95	91
I gained valuable knowledge related to machine learning	94	95	100	87
I networked with other students in my discipline	92	85	95	96
I gained experience that will be helpful in getting me an internship	84	85	84	83
I gained experience that will be helpful in getting a job	82	80	84	83
I established valuable contacts and relationships with faculty in my discipline	79	65	89	83
I learned something useful for my other classes	77	90	63	78
This experience will be helpful if/when applying to graduate degree programs	73	55	84	78
I became more interested in a career related to machine learning	69	75	74	61
The course helped me figure out what I want to do in the future	66	60	74	65
Other (briefly explain) -Grateful to have gained valuable skills that I can build on -learned the importance of technical presentations	3	0	0	9

Post Course Feedback

Student post-course feedback was very positive with an average response of 4.15 and 10 of the 12 items below averaging 4 or above for the overall sample. While getting a stipend was important (M=4.44), students also strongly agreed that they established strong relationships with faculty and will keep in touch (M=4.31), planned to keep in touch with students they met (M=4.34) and are better prepared for the coming year after completing this course (M=4.34)

	Overall Sample (N=62)		Arkansas (n=20)		Kentucky (n=19)		Morgan State (n=23)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Overall Scale	4.15	.51	4.17	.42	4.31	.53	3.98	.53
It was very important to me that I received course credit for this course	4.03	1.086	4.15	1.137	3.79	1.182	4.13	.968
Getting a stipend was important to me.	4.44	.822	4.45	.759	4.53	.841	4.35	.885
I found the residential experience to be very enjoyable	4.02	.949	4.00	.973	4.42	.769	3.70	.974
I would enroll in a refresher course if available	4.00	1.040	3.95	.999	4.16	1.214	3.91	.949
I am more likely to join a professional organization now	4.26	.808	4.35	.671	4.53	.697	3.96	.928
I plan to keep in touch with other students I met in this course.	4.34	.745	4.30	.571	4.42	1.017	4.30	.635
I established strong relationships with the faculty from this course and will keep in touch.	4.31	.737	4.15	.813	4.68	.582	4.13	.694
I will keep in touch with the teaching assistants from this course.	3.97	.868	3.80	.894	4.11	.994	4.00	.739
I plan to continue work on the capstone project from this course.	3.51	1.233	3.60	1.142	3.84	1.167	3.14	1.32 0
I am interested in other learning opportunities to help me retain what I learned in this course.	4.24	.843	4.45	.759	4.47	.612	3.87	.968
I would recommend other coursework related to machine learning to my peers.	4.27	.793	4.45	.686	4.37	.831	4.04	.825
I will be better prepared for the coming year after completing this course.	4.34	.676	4.40	.598	4.47	.697	4.17	.717
5-point Agreement Scale (SD, D, N, A, SA)								

Retrospective Pre-Post Perceptions

Students were asked to indicate the evaluate their knowledge and abilities in comparison to the beginning of the course using a 5-point scale (1=much worse, 3= about the same, 5=much better). Students' retrospective pre-post feedback was very positive with an overall average of 4.08 and all items averaging above 3.8 with 9 of the 15 above 4.0. Students expressed the most improvement in their confidence that they will get a job earn and advanced degree upon graduation (M=4.40) and their awareness of potential careers in machine learning (M=4.31).

	Overall Sample (N=62)		Arkansas (n=20)		Kentucky (n=19)		Morgan State (n=23)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Overall Scale	4.08	.56	4.14	.53	4.15	.56	3.96	.59
My interest in machine learning	4.11	.889	4.30	.733	4.32	.885	3.78	.951
My belief that I will succeed in school	4.13	.778	3.95	.945	4.32	.749	4.13	.626
My awareness of potential careers in machine learning	4.31	.531	4.30	.571	4.42	.507	4.22	.518
My ability to work effectively with others	4.13	.747	4.22	.732	4.16	.834	4.04	.706
My ability to engage in problem-solving	4.16	.706	4.30	.733	4.00	.745	4.17	.650
My communication skills	4.03	.774	4.16	.688	3.95	.911	4.00	.739
My leadership ability	3.95	.798	4.10	.718	3.68	.885	4.04	.767
My ability to think of creative solutions to real issues	4.21	.681	4.30	.657	4.26	.653	4.09	.733
My time management skills	3.92	.775	4.05	.686	3.84	.898	3.87	.757
My interest in a a career related to machine learning	3.94	1.054	4.05	1.050	4.21	.855	3.61	1.158
Use of effective study skills	3.87	.713	3.95	.605	3.79	.787	3.87	.757
My intention to enroll in more machine learning related courses	3.90	1.060	3.95	.911	4.37	1.012	3.48	1.082
My intention to seek internship or other opportunities related to machine learning	3.97	1.040	4.05	.826	4.42	.961	3.52	1.123
My commitment to complete my degree.	4.15	.846	4.10	.912	4.16	.898	4.17	.778
My confidence that I will get a job or an advanced degree upon graduation.	4.40	.712	4.35	.671	4.42	.838	4.43	.662

Scale (1=much worse, 3-=about the same, 5=much better)

Culturally Responsive Teaching

Students were asked to respond to two scales focused on culturally responsive teaching. These scales included the Culturally Responsive Teaching Self-Efficacy Scale (CRTSE) and the Culturally Responsive Teaching Outcome Expectations Scale (CRTOE) (Siwatu, K., 2007). These instruments were developed for preservice teachers and modified form use in college teaching.

Culturally Responsive Teaching Self-Efficacy (CRTSE) – Students responded to the CRTSE in relation to the instruction they observed in the course. Overall, students perceived the teaching in the course to be culturally responsive with an overall scale average of 3.93 (using a 5-point scale) and all 27 items averaging above 3.5. Students most strongly agreed that their instructors explained new concepts using examples taken from students' everyday lives (M=4.15), built a sense of trust in students (M=4.16) and developed personal relationships with students (M=4.23). Students at Kentucky reported the highest levels of culturally responsive teaching with an overall average of 4.29 and all but one item exceeding 4.0.

Culturally Responsive Teaching Efficacy	Overall Sample (N=62)		Arkansas (n=20)		Kentucky (n=19)		Morgan State (n=23)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Overall Scale	3.93	.83	3.87	1.01	4.29	.59	3.67	.75
The instructors in this course:								
adapted instruction to meet the needs of students	4.03	.948	4.15	.875	4.21	.976	3.77	.973
learned about students' academic strengths	3.93	1.031	4.00	1.076	4.26	.872	3.59	1.054
determined whether students prefer working alone or in groups	3.62	1.213	3.80	1.196	3.63	1.422	3.45	1.057
determined whether students felt comfortable competing with other students	3.78	1.121	3.95	1.234	4.00	1.106	3.43	.978
identified ways that the school/ university culture (e.g. values, norms, and practices) is different from students' home culture.	3.87	1.132	3.70	1.380	4.37	.895	3.59	.959
implemented strategies to minimize the effects of the mismatch with the overall school/university culture.	3.74	1.079	3.55	1.191	4.21	.918	3.50	1.012
assessed student learning using a variety of assessment approaches	3.84	1.113	3.85	1.040	4.11	1.049	3.59	1.221
built a sense of trust in students	4.16	.860	4.05	.945	4.58	.607	3.91	.868
used a variety of instructional approaches	3.87	1.112	4.05	1.191	4.00	1.138	3.59	1.008
developed a community of learners when my class consists of students from diverse backgrounds	4.00	.856	3.90	.912	4.47	.612	3.68	.839
drew upon students' cultural background to help make learning meaningful	3.85	1.078	3.60	1.353	4.32	.885	3.68	.839

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Culturally Responsive Teaching

(Continued from Page 25)

drew upon students' prior knowledge to help them make sense of the information	3.98	.885	4.10	.912	4.32	.820	3.59	.796
learned more about students' cultural background	3.80	1.077	3.65	1.387	4.32	.749	3.50	.859
discussed ways in which different cultures made contributions to the field	3.97	1.134	3.84	1.214	4.37	.895	3.73	1.202
established a class environment that reflects a variety of cultures	3.98	.957	3.80	1.152	4.37	.761	3.82	.853
developed personal relationships with students	4.23	.824	4.05	.999	4.68	.582	4.00	.690
understood students' academic weaknesses	3.87	1.087	3.85	1.182	4.21	1.032	3.59	1.008
helped students establish positive relationships with other students in class	4.02	.806	3.95	.887	4.37	.761	3.77	.685
used instructional materials to included representation of cultural groups	3.87	.991	3.65	1.226	4.32	.820	3.68	.780
show how various cultural groups have used the course content	3.79	1.142	3.65	1.348	4.26	1.046	3.50	.913
helped students feel like important members of the class	3.98	.975	3.80	1.056	4.47	.697	3.73	.985
used examples in class that are familiar to students from diverse backgrounds	3.89	1.018	3.80	1.105	4.16	1.119	3.73	.827
explained new concepts using examples taken from students' everyday lives	4.15	.910	4.10	1.071	4.47	.697	3.91	.868
understood student's' academic interests	4.07	.854	3.95	1.050	4.47	.697	3.82	.664
used the interests of students to make learning meaningful for them	4.03	.930	3.95	1.050	4.42	.769	3.77	.869
implemented cooperative learning activities for those who like to work in groups	4.00	.876	3.90	1.021	4.47	.697	3.68	.716
designed instruction that matches students' developmental needs	3.79	1.097	3.75	.967	4.11	1.197	3.55	1.101
Scale (1=not at all, 5=A great extent)								

Culturally Responsive Teaching Outcome Expectations Scale (CRTOE)

Students' responses to the CRTOE were in terms of what outcomes they might expect from culturally responsive teaching approaches. Overall, students strongly agreed that culturally responsive teaching would be expected to result in positive outcomes with an overall scale average response of 4.45 (using a 5-point scale). Furthermore, all 20 items averaged 4.0 or above. More specifically, students strongly agreed that when students see themselves in the pictures and examples used in class, they develop a positive self-identity (M=4.52), using a variety of instructional approaches helps students be successful (M=4.54), students are more motivated and engaged when a personal relationship is established between the instructor and student (M=4.55) and students will be successful when instruction is adapted to meet their needs (M=4.57). While the overall sample had positive expectations, average responses from students at Kentucky and Morgan State were slightly higher.

	Overall Sample (N=62)		Arkansas (n=20)		Kentucky (n=19)		Morgan State (n=23)	
Outcome Expectancy Beliefs	Mean	SD	Mean	SD	Mea n	SD	Mean	SD
Overall Scale	4.45	.52	4.28	.59	4.67	.40	4.42	.48
A positive teacher-student relationship can be established by building a sense of trust in my students.	4.49	.744	4.25	.967	4.89	.315	4.36	.658
Using a variety of instructional methods will help students be successful.	4.54	.594	4.30	.657	4.95	.229	4.41	.590
Students will be successful when instruction is adapted to meet their needs.	4.57	.644	4.35	.745	4.84	.375	4.55	.671
Developing a community of learners promotes positive interactions between students	4.49	.649	4.40	.681	4.68	.582	4.41	.666
Acknowledging the ways that the school/university culture is different from students' home culture helps to keep students engaged.	4.38	.734	4.25	.716	4.58	.769	4.32	.716
It is important to understand and use ng the communication preferences of my students to minimize communication problems.	4.34	.704	4.15	.745	4.74	.452	4.18	.733
Connecting students' prior knowledge with new information will lead to deeper learning.	4.43	.763	4.10	.968	4.74	.562	4.45	.596
Matching instruction to students' learning preferences will enhance their learning.	4.44	.671	4.15	.745	4.74	.452	4.45	.671
Revising instructional materials to include better representation of students' cultural groups will foster positive self-images.	4.43	.718	4.10	.718	4.58	.692	4.59	.666
Students will develop an appreciation for their culture when they are taught about the contributions their culture has made.	4.34	.854	4.05	.759	4.42	1.071	4.55	.671

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Culturally Responsive Teaching Outcome Expectations Scale (CRTOE)

(Continued from Page 27)

The likelihood of a student-teacher misunderstanding decreases when students' cultural background is understood.	4.41	.761	4.35	.745	4.53	.841	4.36	.727
Adapting the structure of the class to be compatible with my students' home culture increases student motivation to engage in class.	4.36	.708	4.15	.671	4.42	.769	4.50	.673
Students are more motivated and engaged when a personal relationship is established between the instructor and student.	4.55	.746	4.40	.681	4.63	.955	4.62	.590
Using a variety of assessment approaches provides a better picture of what students have learned.	4.48	.595	4.50	.607	4.63	.496	4.32	.646
Drawing from students' interests when designing instruction increases student motivation to learn.	4.41	.783	4.25	.786	4.63	.684	4.36	.848
Students' self-esteem is enhanced when their cultural background is valued my the instructor.	4.44	.676	4.35	.671	4.68	.582	4.30	.733
Helping students from diverse cultural backgrounds succeed in school will increase their confidence in their academic abilities.	4.44	.719	4.40	.754	4.58	.692	4.36	.727
Students academic achievement will increase when they are provided with unbiased access to learning resources.	4.46	.697	4.35	.745	4.63	.684	4.41	.666
Using culturally familiar examples makes learning new concepts easier.	4.48	.698	4.40	.681	4.68	.671	4.36	.727
When students see themselves in the pictures and examples used in class, they develop a positive self-identity.	4.52	.648	4.40	.681	4.74	.562	4.45	.671
5-point agreement scale (SD, D, N, A, SA)								

Confidence in Machine Learning Student Learning Outcomes

As might be expected, students were more confident in comparison to what they reported at the beginning of the course, with items averaging approximately 4 or above (using a 5-point scale. Overall, they indicated the greatest confidence in their ability to investigate, clean and visualize data (M=4.15).

	Overall Sample (N=62)		Arkansas (n=20)		Kentucky (n=19)		Morgan State (n=23)	
ML Course SLO	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Overall Scale	4.05	.66	4.16	.76	4.25	.59	3.79	.57
Investigate. clean and visualize data	4.15	.833	4.20	.768	4.21	1.032	4.05	.722
Understand and frame a problem as a supervised machine learning problem including whether it is a regression or classification problem and to incorporate the application requirements	3.95	.902	4.25	.786	4.11	1.100	3.55	.671
Apply and tune common machine learning (ML) models in Python by making use of multiple ML toolkits	4.07	.793	4.15	.875	4.37	.597	3.73	.767
Demonstrate the ability to qualitatively and quantitatively evaluate the quality of trained regression and classification models	4.05	.845	4.15	.933	4.32	.749	3.73	.767
Communicate technical concepts (oral and written) for an audience who may have limited technical background	4.05	.825	4.15	.933	4.21	.787	3.82	.733
Identify the potential bias in ML models and explain its implications	4.05	.805	4.05	.826	4.26	.733	3.86	.834
Scale (1=Not at all, 5=A great extent)								

Confidence in ABET Student Learning Outcomes

At the end of the course, students also expressed higher levels of confidence in their knowledge and ability related to the ABET student learning outcomes with all responses averaging above 4.0. They reported the greatest confidence in relation to understanding their professional and ethical responsibilities (M=4.30), applying knowledge of math, science and engineering (M=4.27), and ability to use the techniques, skills, and modern engineering tools necessary for engineering practice (M=4.27).

	Overall Sample (N=62)		Arkansas (n=20)		Kentucky (n=19)		Morgan State (n=23)	
ABET SLO	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Overall Scale	4.18	.63	4.32	.68	4.33	.57	3.94	.57
Apply knowledge of mathematics, science and engineering	4.27	.756	4.35	.745	4.39	.778	4.09	.750
Design and conduct experiments and interpret the resulting data	4.17	.763	4.30	.923	4.39	.608	3.86	.640
Design a system, component, or process to meet desired needs	4.02	.892	4.30	.865	4.11	1.079	3.68	.646
Work effectively on a multidisciplinary team	4.14	.880	4.16	1.119	4.33	.767	3.95	.722
Identify, formulate and solve engineering problems	4.13	.747	4.40	.681	4.28	.752	3.77	.685
Understand professional and ethical responsibility	4.30	.720	4.40	.681	4.39	.608	4.14	.834
Communicate effectively	4.15	.860	4.35	.813	4.22	.943	3.91	.811
Understand the broad impact of engineering solutions in a global, economic, environmental and social context	4.20	.819	4.20	.834	4.33	.840	4.09	.811
Recognize the need for and ability to engage in professional development/ improvement	4.25	.728	4.40	.754	4.33	.686	4.05	.722
Understanding and awareness of contemporary issues	4.12	.790	4.26	.806	4.33	.686	3.82	.795
Ability to use the techniques, skills, and modern engineering tools necessary for engineering practice.	4.27	.778	4.35	.875	4.56	.511	3.95	.785
Scale (1=Not at all, 5=A great extent)								

Confidence in Machine Learning Units and Topics

Students were asked to indicate the extent to which they confident in their knowledge and ability related to each of the units and topics to be addressed in the Applied Machine Learning Course. Consistent with their confidence in the overall student learning outcomes, students were much more confident in their knowledge and abilities in comparison to the beginning of the course.

	Overall Sample (N=62)		Arkansas (n=20)		Kentucky (n=19)		Morgan State (n=23)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Overall Topics and Units	3.68	.73	3.87	.66	3.98	.58	3.23	.73
Computer Science	3.79	1.002	4.00	.918	4.11	.737	3.32	1.129
Python	3.95	.825	3.95	.887	4.32	.582	3.64	.848
Straight Line Equation	3.87	.974	3.90	.912	4.26	.933	3.50	.964
Functions	4.02	.940	4.05	.887	4.42	.692	3.64	1.049
Matrix Algebra	3.57	1.040	3.55	1.050	4.11	.937	3.14	.941
Normal Distribution Properties	3.80	.872	4.00	.973	4.00	.882	3.45	.671
Hypothesis Testing	3.85	.928	3.95	.887	4.26	.733	3.41	.959
Probability and p-values	3.68	1.000	4.11	.809	3.84	1.167	3.18	.795
Data Science	3.59	.844	3.55	.686	4.05	.911	3.23	.752
Types of Machine Learning (ML) Models	3.87	.846	4.00	.725	4.26	.452	3.41	1.008
Ethical Consequences of Machine Learning	4.18	.847	4.15	.813	4.53	.513	3.91	1.019
Data Analysis and Manipulation - Colab notebooks	4.15	.813	4.30	.733	4.47	.612	3.73	.883
Data Analysis and Manipulation -Panda Series and Panda DataFrames	4.05	.865	3.95	.887	4.63	.496	3.64	.848
Visualization of data	4.18	.785	4.25	.716	4.58	.507	3.77	.869
Acquiring and downloading data	4.32	.813	4.30	.733	4.61	.608	4.09	.971
Exploratory data analysis	4.21	.859	4.40	.754	4.32	.749	3.95	.999
Regression analysis	3.75	.943	3.85	.933	4.26	.653	3.23	.922

(Continued on Page 32)

Confidence in Machine Learning Units and Topics

(Continued from Page 31)

Using scikit-learn for regression analysis	3.82	.904	3.95	.759	4.42	.607	3.18	.853
Using TensorFlow	3.79	.839	3.95	.826	4.21	.713	3.27	.703
Binary Classification methods	3.85	.872	3.95	.945	4.21	.631	3.45	.858
Multiclass Classification	3.79	.878	3.90	.852	4.26	.733	3.27	.767
Image - Video Classification	3.74	.964	4.10	.912	4.05	.780	3.14	.889
Deep Learning	3.68	.937	3.89	.875	4.00	1.000	3.19	.750
Recurrent Neural Network	3.49	.994	3.90	.852	3.63	.895	3.00	1.024
Natural Language Processing	3.42	1.030	3.65	.875	3.63	1.012	3.00	1.095
Transfer Learning	3.47	1.065	3.85	.933	3.68	1.003	2.90	1.044
Clustering	3.59	1.023	3.90	.912	3.95	.705	3.00	1.113
k-Means models	3.56	1.025	3.70	.979	4.05	.780	3.00	1.024
Embedding	3.48	1.026	3.70	1.031	3.79	.918	3.00	.976
Decision Trees and Random Forest	3.52	1.043	4.00	.858	3.74	.933	2.91	1.019
Bayesian Modeling	3.11	1.127	3.45	.945	3.21	1.357	2.73	.985
Support Vector Machines (SVM)	3.13	1.087	3.30	.979	3.16	1.344	2.95	.950
XG Boost	3.05	1.156	3.35	1.226	3.00	1.291	2.81	.928
Activation Functions	3.37	1.008	3.58	.769	3.63	1.065	2.95	1.046
Big O	3.23	1.198	3.42	1.121	3.53	1.219	2.82	1.181
Dimensionality Reduction	3.15	1.138	3.55	.826	3.21	1.398	2.73	1.032
Loss Functions	3.38	1.067	3.75	.786	3.68	1.157	2.77	.973
Probability and Statistics	3.64	1.096	4.05	1.050	3.95	.848	3.00	1.069
Regular Expressions	3.33	1.130	3.75	1.164	3.33	1.085	2.95	1.046
Scale (1=Not at all, 5= A great extent)								

Engineering Self-Efficacy

In general, students indicated high levels of confidence related to engineering with all but two items averaging 4.0 or above (using a 5-point scale). Overall, students indicated the greatest efficacy related to general engineering (M=4.49) and engineering skills (M=4.41)

	Overall Sample (N=62)		Arkansas (n=20)		Kentucky (n=19)		Morgan State (n=23)	
Engineering Self-Efficacy	Mean	SD	Mean	SD	Mean	SD	Mean	SD
General Self-Efficacy	4.49	.61	4.53	.67	4.61	.55	4.35	.58
I can master the content in my major courses	4.57	.590	4.75	.550	4.74	.452	4.27	.631
I can master the content in even the most challenging engineering course	4.44	.696	4.50	.688	4.68	.582	4.18	.733
I can do good work in my major coursework	4.59	.588	4.55	.686	4.68	.478	4.55	.596
I can do an excellent job on engineering-related problems or tasks I am assigned	4.46	.697	4.50	.761	4.47	.697	4.41	.666
I can learn the content taught in my engineering-related courses	4.44	.719	4.45	.826	4.53	.697	4.36	.658
I can earn good grades in my engineering-related courses	4.43	.805	4.45	.887	4.53	.841	4.32	.716
Engineering Skills Self-Efficacy	4.41	.57	4.47	.59	4.58	.49	4.21	.59
I can perform experiments independently	4.34	.750	4.35	.745	4.53	.841	4.18	.664
I can analyze data from experiments	4.43	.670	4.45	.759	4.68	.478	4.18	.664
I can orally communicate results from experiments	4.33	.811	4.40	.754	4.37	1.012	4.23	.685
I can communicate results in written form	4.43	.673	4.55	.759	4.63	.496	4.14	.655
I can solve problems using a computer	4.51	.649	4.60	.681	4.68	.478	4.27	.703
Design Self-Efficacy	4.27	.71	4.22	.78	4.48	.74	4.14	.58
I can design new things	4.27	.800	4.15	.933	4.42	.769	4.24	.700

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Engineering Self-Efficacy

(Continued from Page 33)

I can identify a design need	4.37	.712	4.35	.745	4.56	.705	4.23	.685
I can develop design solutions	4.23	.804	4.15	.933	4.42	.769	4.14	.710
I can evaluate a design	4.31	.807	4.30	.801	4.53	.905	4.14	.710
I can reorganize changes needed for a design solution to work	4.18	.785	4.15	.875	4.47	.772	3.95	.653
Tinkering Self-Efficacy	4.13	.82	4.15	.77	4.19	1.01	4.05	.59
I can work with tools and use them to build things	4.23	.902	4.15	.933	4.53	1.020	4.05	.722
I can work with tools and use them to fix things	4.23	.902	4.20	.834	4.42	1.071	4.09	.811
I can work with machines	4.26	.893	4.20	.894	4.47	1.073	4.14	.710
I can fix machines	3.80	1.138	3.85	1.14	3.79	1.512	3.77	.752
I can manipulate components and devices	3.98	.991	3.95	.945	3.89	1.370	4.09	.610
I can assemble things	4.20	.891	4.35	.745	4.11	1.286	4.14	.560
I can disassemble things	4.18	.940	4.35	.813	4.11	1.286	4.09	.684
I can apply technical concepts in engineering	4.30	.926	4.35	.875	4.26	1.195	4.29	.717
Scale (1=SD,2=D, 3=N, 4=A, 5=SA)								

Persistence

At the end of the course, students indicated a strong intention to persist with 10 of the 14 items averaging 4 or above. More specifically, they indicated that they planned to take courses in their major next year (M=4.69), complete their current degree (M=4.63), continue their education in their current field (M=4.56), get a job in their major field (M=4.70) and working in the field for at least 5 years (M=4.57).

	Overall Sample (N=62)		Arkansas (n=20)		Kentucky (n=19)		Morgan State (n=23)	
Intention to Persist	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Overall Scale	4.20	.65	4.31	.73	4.31	.57	4.01	.62
Next year, I plan to take courses in my major discipline	4.69	.620	4.75	.550	4.95	.229	4.41	.796
I intend to get my degree in my current major	4.63	.688	4.65	.745	4.79	.535	4.48	.750
I am sure that I will continue my education in my major field	4.56	.807	4.75	.550	4.53	.841	4.41	.959
I intend to get an advanced degree in my major field	4.13	1.103	3.90	1.294	4.42	1.121	4.09	.868
I plan to pursue and secure an internship this year.	4.43	.945	4.58	.769	4.32	1.293	4.41	.734
I intend to get a job in my major field	4.70	.615	4.70	.571	4.84	.501	4.59	.734
I can see myself working in my current field for at least 5 years.	4.57	.694	4.55	.759	4.63	.597	4.55	.739
I plan to devote my career to my current major discipline	4.51	.744	4.50	.761	4.58	.692	4.45	.800
I plan to take additional courses related to machine learning.	4.26	.982	4.45	.945	4.42	.769	3.95	1.133
I intend to seek internship opportunities related to machine learning	4.02	1.118	4.15	1.089	4.21	1.032	3.73	1.202
I am considering changing my major to something more directly related to machine learning	3.36	1.472	3.70	1.455	3.32	1.565	3.09	1.411
I plan to pursue an advanced degree related to machine learning	3.56	1.409	3.80	1.436	3.74	1.195	3.18	1.532
I plan to get a job related to machine learning.	3.64	1.239	3.90	1.252	3.63	1.300	3.41	1.182
I would like to have a career related to machine learning	3.75	1.220	3.95	1.317	3.89	1.150	3.45	1.184
1=Not TRUE of me , 5=VERY TRUE of me								

Job Search and Career Preparation Skills

At the end of the course, students indicated a high level of confidence with all items averaging above 3.5 (using a 5-point scale). Students expressed the most confidence in their ability to receive and use feedback from others (M=4.20), prepare for giving a presentation (M=4.11), and apply for internship or job opportunities (M=4.10).

	Overall Sample (N=62)		Arkansas (n=20)		Kentucky (n=19)		Morgan State (n=23)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Overall Scale	3.99	.79	3.99	.86	4.04	.82	3.96	.73
Constructing a resume	3.89	1.066	3.95	.999	3.89	1.197	3.82	1.053
Meeting and engaging with professionals in your field	3.98	.885	3.95	.945	4.05	.911	3.95	.844
Giving feedback to others	4.02	.892	3.95	.911	4.32	.749	3.82	.958
Receiving and using feedback from others	4.20	.813	4.25	.910	4.32	.671	4.05	.844
Working with recruiters or career services related to potential jobs	3.85	.997	4.00	1.026	3.95	1.079	3.64	.902
Talking with faculty and others about potential internship of job opportunities	3.97	.912	3.95	.887	4.00	1.000	3.95	.899
Preparing application materials for an internship or job	3.93	.989	3.90	.912	4.05	.970	3.86	1.108
Preparing for a job interview	4.02	.873	4.00	.918	4.06	.938	4.00	.816
Interviewing for an internship or job	3.92	1.021	3.90	1.021	3.84	1.119	4.00	.976
Preparing for a presentation you will do	4.11	.950	4.15	.988	4.00	1.106	4.18	.795
Delivering a strong oral presentation with confidence	3.90	1.165	3.90	1.119	3.68	1.376	4.09	1.019
Learning about sources for potential internships or jobs	4.08	.862	4.00	.858	4.16	.898	4.09	.868
Applying for an internship or job opportunity	4.10	.858	4.05	.945	4.22	.808	4.05	.844
1=Not at all, 5=A great extent								

Career Readiness Competencies

At the end on the course, students expressed high levels of confidence in relation to the eight competencies of career readiness in the table below. Overall, students expressed the greatest confidence in their abilities in terms of technology (M=4.30), teamwork (M=4.26), professionalism (M=4.26) and critical thinking (M=4.26).

	Overall Sample (N=62)		Arkansas (n=20)		Kentucky (n=19)		Morgan State (n=23)	
Career Readiness Competencies	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Overall Readiness Scale	4.20	.64	4.18	.68	4.24	.68	4.19	.59
Career and Self-Development - Awareness of strengths and weaknesses and seek relationships with professionals and opportunities to better prepare you for a career.	4.11	.819	4.00	1.02 6	4.21	.713	4.14	.710
Communication - Able to clearly exchange information, ideas, facts, and perspectives wit people inside and outside of my current institution or organization.	4.10	.889	4.05	.887	4.05	1.079	4.18	.733
Critical Thinking - Identify and respond to needs based upon an understanding of the context and a logical analysis of relevant information.	4.28	.777	4.35	.933	4.37	.684	4.14	.710
Equity and Inclusion - Demonstrate an awareness, attitude, knowledge, and skills required to equitably engage and include people from different cultures.	4.25	.699	4.30	.657	4.42	.692	4.05	.722
Leadership - Recognize and Capitalize on personal and team strengths to achieve organizational goals.	4.03	.912	3.95	.999	4.00	1.106	4.14	.640
Professionalism - Knowing work environments differ greatly, understand and demonstrate effective work habits, and act in the interest of the larger community and workplace.	4.26	.772	4.30	.733	4.21	.855	4.27	.767
Teamwork - Build and maintain collaborative relationships to work effectively toward common goals, while appreciating diverse viewpoints and share responsibilities.	4.26	.854	4.20	.834	4.32	1.057	4.27	.703
Technology - Understand and leverage technology ethically to enhance efficiency, complete tasks and accomplish goals.	4.30	.715	4.25	.786	4.32	.582	4.32	.780
1-Not at all, 5=A great extent								

Career Interests

Finally, students were asked to indicate their interest in specific careers related to machine learning. Of the 10 careers listed below, students expressed the greatest interest in software engineering (M=3.84),), software programming (M=3.30) and software development (M=3.79). Students at Kentucky also expressed great interest in a career as a machine learning engineer (M=4.21).

	Overall Sample (N=62)		Arkansas (n=20)		Kentucky (n=19)		Morgan State (n=23)	
Career Interests	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Software Engineer	3.84	1.214	4.10	.718	4.26	1.147	3.23	1.412
Software Programmer	3.80	1.219	4.05	.945	4.28	.958	3.18	1.402
Software Developer	3.79	1.226	4.05	.945	4.16	1.068	3.23	1.412
Data Scientist	3.54	1.119	3.70	.923	3.95	.970	3.05	1.253
Computer Engineer	3.46	1.246	3.65	1.040	3.63	1.342	3.14	1.320
Artificial Intelligence Research Scientist	3.59	1.116	3.85	.813	4.00	.943	3.00	1.272
Cloud Engineer	3.22	1.250	3.25	1.118	3.53	1.124	2.90	1.446
Machine Learning Scientist	3.39	1.269	3.55	1.276	3.95	1.026	2.77	1.232
Machine Learning Engineer	3.56	1.285	3.75	1.293	4.21	.855	2.82	1.259
Big Data Engineer	3.26	1.223	3.45	1.395	3.37	1.165	3.00	1.113
1=Not at all interested, 5=Very interested								

Pre-Post Course Change

Finally, comparisons were made from the pre course to post course survey administrations using a matched sample. These comparisons are summarized in the table below. All averages were higher at the end of the course, indicating improvement. Of the 11 comparisons summarized below, 9 reached the minimum criteria for statistical significance (< .05). These comparisons were also examined in terms of magnitude (effect size) with 2 large effects for changes directly related to the machine learning course. That is, students significantly improved their confidence in meeting the ML course student learning outcomes and their confidence related to the course units. In addition, students also reported significant higher engineering efficacy, confidence in meeting the ABET SLOs and persistence at the end of the course.

		Pre Couse	Post Course		
Scale	**N**	**Mean (SD)**	**Mean (SD)**	**t (p)**	**Effect Size (Cohen's d)[a]**
ML Course SLOs	59	2.21 (.94)	4.04 (.67)	14.22 (<.001)	1.87
ABET SLOs	58	3.69 (.83)	4.18 (.63)	4.5 (< .001)	.591
MK Course Unit Confidence	59	2.17 (.73)	3.67 (.74)	14.35 (<.001)	1.87
Engineering Efficacy – Total	59	3.99 (.61)	4.32 (.59)	4.18 (<.001)	.544
General	59	4.21 (.60)	4.49 (.60)	3.32 (<.001)	.432
Skills	59	4.14 (.65)	4.42 (.58)	3.55 (<.001)	.463
Design	59	3.88 (.78)	4.27 (.71)	4.14 (<.001)	.539
Tinkering	59	3.79 (.92)	4.13 (.82)	3.09 (.002)	.402
Persistence	59	4.02 (.57)	4.19 (.66)	1.93 (.029)	.252
Career Development Units	58	3.91 (.76)	3.99 (.80)	.767 (.223)	.101
Career Readiness	59	4.08 (.69)	4.22 (.64)	1.58 (.060)	.205
a-.2=small, .5=medium, .8=large					

Follow-up Pre-Post Comparisons

Follow-up comparisons were made on items from each of the scales that resulted in a statistically significant improvement. Confidence in Machine Learning Student Learning Outcomes – Means and standard deviations for each of the course student learning outcomes are summarized below for the matched sample of 59 students. Each of the six comparisons was statistically significant with students reporting greater confidence in their ability in their ability at the end of the course.

	Pre Course (n=59)		Post Course (n=59)		
ML Course SLO	Mean	SD	Mean	SD	*t*
Overall Scale	2.21	.94	4.04	.67	
Investigate. clean and visualize data	2.92	1.263	4.15	.847	6.370***
Understand and frame a problem as a supervised machine learning problem including whether it is a regression or classification problem and to incorporate the application requirements	2.05	1.166	3.95	.918	9.939***
Apply and tune common machine learning (ML) models in Python by making use of multiple ML toolkits	1.78	1.052	4.05	.797	14.600***
Demonstrate the ability to qualitatively and quantitatively evaluate the quality of trained regression and classification models	1.95	1.090	4.03	.850	12.335***
Communicate technical concepts (oral and written) for an audience who may have limited technical background	2.68	1.319	4.05	.839	7.955***
Identify the potential bias in ML models and explain its implications	1.86	.991	4.03	.809	13.564***
Scale (1=Not at all, 5=A great extent) *p<.05, **p<.01,*** p <.001					

Confidence in ABET Student Learning Outcomes

As with the course SLOs, students' confidence related to the 11 ABET SLOs was compared from pre course to post course. Students reported greater confidence for each of these SLOs at the end od the course. Of the 11, 9 were statistically significant.

	Pre Course (N=58)		Post Course (n=58)		
ABET SLO	Mean	SD	Mean	SD	t
Overall Scale	3.69	.83	4.18	.63	
Apply knowledge of mathematics, science and engineering	3.66	1.027	4.26	.762	4.642***
Design and conduct experiments and interpret the resulting data	3.48	1.186	4.17	.775	4.081**
Design a system, component, or process to meet desired needs	3.39	1.175	4.00	.898	3.843***
Work effectively on a multidisciplinary team	3.92	1.094	4.14	.895	1.196
Identify, formulate and solve engineering problems	3.42	1.037	4.12	.751	4.810***
Understand professional and ethical responsibility	3.98	1.042	4.29	.726	2.023*
Communicate effectively	4.14	.907	4.16	.875	.248
Understand the broad impact of engineering solutions in a global, economic, environmental and social context	3.65	1.087	4.19	.826	3.539***
Recognize the need for and ability to engage in professional development/improvement	3.87	.999	4.26	.739	3.297**
Understanding and awareness of contemporary issues	3.65	.988	4.12	.803	3.643***
Ability to use the techniques, skills, and modern engineering tools necessary for engineering practice.	3.60	1.028	4.26	.785	4.406***
Scale (1=Not at all, 5=A great extent) *p<.05, **p<.01,*** p <.001					

Confidence in Machine Learning Units and Topics

Follow-up comparisons for each of the 39 topics summarized below yielded statistically significant improvement in student confidence for all but one. That unit was the unit on functions for which students expressed a high level of confidence prior to the course and maintained that confidence throughout the course.

	(N=59)		(n=59)		
	Mean	SD	Mean	SD	t
Overall Topics and Units	2.17	.73	3.67	.74	
Computer Science	3.07	1.127	3.78	1.018	5.188***
Python	2.70	1.183	3.93	.828	8.778***
Straight Line Equation	3.07	1.461	3.86	.973	3.657***
Functions	3.72	1.091	4.00	.947	1.932
Matrix Algebra	2.73	1.201	3.54	1.039	4.733***
Normal Distribution Properties	2.87	1.268	3.78	.872	5.138***
Hypothesis Testing	3.12	1.274	3.83	.931	4.434***
Probability and p-values	2.93	1.255	3.71	.991	4.910***
Data Science	2.39	1.017	3.59	.853	7.676***
Types of Machine Learning (ML) Models	1.78	.930	3.86	.860	14.486***
Ethical Consequences of Machine Learning	2.16	1.225	4.17	.854	11.619***
Data Analysis and Manipulation - Colab notebooks	1.93	1.096	4.14	.819	12.533***
Data Analysis and Manipulation -Panda Series and Panda DataFrames	1.76	1.056	4.03	.870	13.391***
Visualization of data	2.75	1.195	4.17	.791	8.085***
Acquiring and downloading data	2.91	1.204	4.31	.821	8.370***
Exploratory data analysis	2.34	1.092	4.22	.872	11.230***
Regression analysis	2.19	1.224	3.75	.958	8.015***
Using scikit-learn for regression analysis	1.67	.980	3.80	.906	12.213***
Using TensorFlow	1.47	.838	3.78	.852	16.410***
Binary Classification methods	1.88	1.093	3.86	.880	11.874***
Multiclass Classification	1.83	1.157	3.80	.886	11.030***
Image - Video Classification	1.68	1.003	3.73	.980	11.328***
Deep Learning	1.86	1.131	3.67	.951	9.813***

(Continued on Page 43)

Confidence in Machine Learning Units and Topics

(Continued from Page 42)

Recurrent Neural Network	1.58	.969	3.47	1.006	11.051***
Natural Language Processing	1.79	1.088	3.38	1.023	8.608***
Transfer Learning	1.53	.941	3.45	1.079	11.300***
Clustering	1.83	1.117	3.58	1.037	10.182***
k-Means models	1.71	.991	3.54	1.039	11.384***
Embedding	1.84	1.141	3.47	1.040	9.518***
Decision Trees and Random Forest	1.81	1.083	3.54	1.056	9.666***
Bayesian Modeling	1.59	1.060	3.10	1.140	8.679***
Support Vector Machines (SVM)	1.42	.835	3.12	1.100	10.106***
XG Boost	1.33	.758	3.05	1.161	10.543***
Activation Functions	1.54	.953	3.40	1.008	11.562***
Big O	2.17	1.353	3.21	1.210	6.284***
Dimensionality Reduction	1.49	.898	3.12	1.146	9.851***
Loss Functions	1.60	1.033	3.36	1.079	10.722***
Probability and Statistics	3.03	1.326	3.63	1.113	3.856***
Regular Expressions	2.80	1.270	3.34	1.148	2.690**
Scale (1=Not at all, 5= A great extent) ***p<.05, **p<.01,*** p <.001**					

Engineering Self-Efficacy

Comparisons for each item from the Engineering Self Efficacy scale are summarized below. Statistically significant improvement resulted for 17 of the 24 items. These significant improvements included all 5 items related to engineering design, 6 of the8 items from the tinkering subscale, 3 of the 5 related to skills and 3 of the 6 related to general efficacy.

	Pre Course (N=59)		Post Course (n=59)		
Engineering Self-Efficacy	Mean	SD	Mean	SD	t
General Self-Efficacy	4.21	.60	4.49	.60	
I can master the content in my major courses	4.25	.709	4.58	.593	3.947***
I can master the content in even the most challenging engineering course	3.78	.904	4.44	.702	5.403***
I can do good work in my major coursework	4.38	.761	4.59	.591	1.995
I can do an excellent job on engineering-related problems or tasks I am assigned	4.20	.732	4.46	.703	2.317*
I can learn the content taught in my engineering-related courses	4.37	.688	4.44	.726	.798
I can earn good grades in my engineering-related courses	4.30	.720	4.42	.814	1.044
Engineering Skills Self-Efficacy	4.14	.65	4.42	.58	
I can perform experiments independently	3.85	.954	4.34	.757	3.751***
I can analyze data from experiments	4.15	.820	4.42	.675	2.585*
I can orally communicate results from experiments	4.18	.833	4.39	.695	1.940
I can communicate results in written form	4.25	.795	4.43	.678	1.592
I can solve problems using a computer	4.30	.788	4.51	.653	2.430*
Design Self-Efficacy	3.88	.78	4.27	.71	
I can design new things	4.00	.902	4.26	.807	2.383*
I can identify a design need	3.83	.847	4.36	.718	5.396***
I can develop design solutions	3.93	.821	4.22	.811	2.538*
I can evaluate a design	3.88	.865	4.31	.815	3.806***
I can reorganize changes needed for a design solution to work	3.78	.885	4.17	.791	3.161**
Tinkering Self-Efficacy	3.79	.92	4.13	.82	
I can work with tools and use them to build things	3.88	1.010	4.22	.911	2.200*
I can work with tools and use them to fix things	3.93	.936	4.24	.897	2.257*
I can work with machines	3.90	1.130	4.27	.887	2.442*
I can fix machines	3.27	1.163	3.85	1.127	3.781***
I can manipulate components and devices	3.66	.976	3.97	.999	2.643*
I can assemble things	4.02	1.000	4.19	.900	1.371
I can disassemble things	3.97	1.104	4.20	.906	1.782
I can apply technical concepts in engineering	3.87	1.049	4.29	.937	2.480*
Scale (1=SD,2=D, 3=N, 4=A, 5=SA)					

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Persistence

Students came into the course with high levels of persistence and maintained or slightly improved over the 8 weeks. At the end of the course, students indicated significantly greater intent to get a job in their field, take additional courses related to machine learning, and to consider changing my major to something more directly related to machine learning.

	Pre Course (N=59)		Post Course (n=59)		
Intention to Persist	Mean	SD	Mean	SD	t
Overall Scale	4.02	.57	4.19	.66	
Next year, I plan to take courses in my major discipline	4.51	.774	4.68	.628	1.457
I intend to get my degree in my current major	4.54	.750	4.64	.693	1.062
I am sure that I will continue my education in my major field	4.56	.702	4.56	.815	.000
I intend to get an advanced degree in my major field	4.03	.909	4.12	1.115	.433
I plan to pursue and secure an internship this year.	4.32	.854	4.41	.956	.739
I intend to get a job in my major field	4.43	.831	4.69	.623	2.348*
I can see myself working in my current field for at least 5 years.	4.51	.728	4.58	.700	.629
I plan to devote my career to my current major discipline	4.43	.767	4.51	.751	.600
I plan to take additional courses related to machine learning.	3.90	1.053	4.25	.993	1.991*
I intend to seek internship opportunities related to machine learning	3.88	1.043	4.00	1.130	.687
I am considering changing my major to something more directly related to machine learning	2.93	1.096	3.36	1.494	1.969*
I plan to pursue an advanced degree related to machine learning	3.20	1.132	3.53	1.419	1.634
I plan to get a job related to machine learning.	3.52	1.081	3.63	1.258	.597
I would like to have a career related to machine learning	3.52	.983	3.73	1.229	1.272
1=Not TRUE of me , 5=VERY TRUE of me *p<.05, **p<.01,*** p <.001					

Changes over time by Site

Changes over the duration of the course were also examined for each site. These findings are summarized in the following tables.

University of Arkansas -Over the duration of the course, students from the University of Arkansas reported improvement for 10 of the 11 scales summarized below with statistically significant improvement related to the course SLOs, ABET SLOs and confidence in the course content topic areas.

University of Arkansas		Pre Couse	Post Course		
Scale	N	Mean (SD)	Mean (SD)	t (p)	Effect Size (Cohen's d)[a]
ML Course SLOs	20	2.41 (1.12)	4.16 (.76)	7.29***	1.63
ABET SLOs	20	3.86 (.87)	4.32 (.68)	2.36*	.527
MK Course Unit Confidence	20	2.33 (.85)	3.87 (.66)	11.12***	2.49
Engineering Efficacy – Total	20	4.12 (.56)	4.33 (.66)	1.53	.343
General	20	4.30 (.55)	4.53 (.67)	1.28	.286
Skills	20	4.21 (.63)	4.47 (.59)	1.62	.363
Design	20	4.03 (.67)	4.22 (.78)	1.16	.260
Tinkering	20	3.98 (.71)	4.15 (.77)	1.17	.262
Persistence	20	4.01 (.64)	4.31 (.73)	1.59	.356
Career Development Units	19	4.01 (.66)	3.98 (.88)	-.196	-.045
Career Readiness	20	4.11 (.71)	4.18 (.69)	.384	.086
*p<.05, **p<.01, ***p<.001 a-.2=small, .5=medium, .8=large					

University of Kentucky - Over the duration of the course, students from the University of Kentucky reported improvement for each of the 11scales summarized below with statistically for significant improvement related to the course SLOs, ABET SLOs, confidence in the course content topic areas, engineering efficacy and career readiness.

University of Kentucky		Pre Couse	Post Course		
Scale	N	Mean (SD)	Mean (SD)	t (p)	Effect Size (Cohen's d)[a]
ML Course SLOs	17	2.31 (.89)	4.25 (.63)	7.51***	1.82
ABET SLOs	17	3.56 (.89)	4.34 (.59)	3.69**	.923
MK Course Unit Confidence	17	2.24 (.73)	3.99 (.62)	8.89***	2.16
Engineering Efficacy – Total	17	3.85 (.52)	4.46 (.62)	3.86**	.937
General	17	4.23 (.58)	4.61 (.55)	2.74*	.664
Skills	17	4.10 (.60)	4.64 (.48)	3.99**	.967
Design	17	3.85 (.77)	4.48 (.77)	3.79**	.921
Tinkering	17	3.42 (.99)	4.22 (1.11)	3.68**	.892
Persistence	17	4.00 (.56)	4.28 (.60)	1.78	.432
Career Development Units	16	3.67 (.95)	4.04 (.86)	1.93	.468
Career Readiness	17	3.84 (.79)	4.31 (.67)	3.13**	.760
***p<.05, **p<.01, ***p<.001 a-.2=small, .5=medium, .8=large**					

Changes over time by Site

Morgan State University -Over the duration of the course, students from the University of Kentucky reported improvement for 8 of the 11scales summarized below with statistically for significant improvement related to the course SLOs, confidence in the course content topic areas, and general and design engineering efficacy

Morgan State University		Pre Couse	Post Course		
Scale	N	Mean (SD)	Mean (SD)	t (p)	Effect Size (Cohen's d)[a]
ML Course SLOs	22	1.96 (.76)	3.79 (.57)	10.18***	2.17
ABET SLOs	22	3.61 (.76)	3.94 (.57)	1.92	.409
MK Course Unit Confidence	22	1.97 (.59)	3.23 (.75)	6.58***	1.40
Engineering Efficacy – Total	22	3.99 (.72)	4.19 (.49)	2.07	.441
General	22	4.12 (.68)	4.35 (.58)	2.17*	.462
Skills	22	4.10 (.73)	4.21 (.59)	1.03	.220
Design	22	3.77 (.89)	4.14 (.58)	2.49*	.533
Tinkering	22	3.94 (.97)	4.05 (.59)	.683	.146
Persistence	22	4.04 (.53)	4.01 (.62)	-.169	-.036
Career Development Units	22	4.01 (.67)	3.97 (.73)	-.352	-.075
Career Readiness	22	4.24 (.55)	4.19 (.59)	-.451	-.098
***p<.05, **p<.01, ***p<.001 a-.2=small, .5=medium, .8=large**					

Focus Group Summary

Focus groups were conducted with students from each of the three institutions during the week of July 18th. All focus groups were conducted virtually, using Zoom.

The primary purpose of these focus groups was to learn more from students about their overall experiences in the course, interactions with other students and faculty, and suggestions to better serve students taking this course.

Overall, students indicated that the overall course was a valuable learning experience. They described it as intense, challenging and fast-paced. Students described the course environment as very collaborative and consistently indicated that one of the most beneficial aspects of the course has been meeting and working collaboratively with their peers from different disciplines. They indicated that the sessions in which a faculty member was present were better that those they watched remotely, but also described the TAs as valuable in helping them. Students offered several suggestions related to the course.

Course Organization and Expectations – Students from each site described that course expectations and details related to required assignments could be more clearly communicated. They suggested an orientation to the class and syllabus so students understand what is expected. They also suggested using a learning management system (LMS) to organize course activities, materials and assignments. There are helpful organizational features within these LMS such as a dashboard that alert participants (students, TAs and instructors) of the course schedule and when upcoming assignments are due. LMS also offer a way to organize course materials and store completed assignments and feedback that might be helpful to review when working on subsequent tasks.

Pre-requisites and Remedial Opportunities – Students indicated that having more experience with programming, statistics and linear Algebra would be beneficial for this course. While some students came in with this experience, others did not. Several students described that they struggled a bit to learn the necessary programming and other background skills to do the work in a timely manner. Students sought help from other students and online resources to try and catch up and keep up with assignments. Students suggested building in opportunities (and perhaps some extra days) for students to engage with more applied examples, resources and get feedback would be very helpful.

Course Projects - Students describing working on projects with other students from diverse backgrounds in terms of race, ethnicity, academic major and academic level. Students described the opportunities they have to work with their peers have been among the most valuable aspect of the course. Working with (and learning from) students in their groups promotes collaboration and teamwork and prepares them for careers in which they will work on projects as part of interdisciplinary teams.
The primary suggestion made was to continue this, but structure teams so that there are students with different backgrounds working together. Also, students want more choices related to the nature of projects on which they work. Also, they suggested introducing the capstone project much earlier in the course so they are better prepared to complete it.

Weekly Feedback Summary

Feedback was gathered each week for weeks 1 to 6. Each week, students responded to items related to the weekly unit objectives, quality of instruction and value of the professional development.

Weekly Objectives – Confidence in Knowledge and Ability

A summary of student responses to their confidence in the weekly objectives is provided below. Generally, as weeks progressed, content became more challenging. While average responses declined slightly over time, averages remained above 3.5 for the first 4 weeks before dipping in week 5 and recovering slightly in week 6.

	# of objectives	Mean	SD	
Week 1	17	3.85	.717	
Week 2	24	3.84	.580	
Week 3	34	3.69	.831	
Week 4	25	3.61	.672	
Week 5	13	3.23	.799	
Week 6	19	3.38	.724	

Quality of Instruction – Students consistently indicated was of high quality with overall average responses of 4 or above in weeks 1 to 5 and just slightly lover (3.93) in week 6. Students believed that instructors demonstrated command of content knowledge, they were learning things useful for their other classes, and they were learning things helpful in preparing them for internships and their career. As weeks progressed, they did have a more difficult tome keep up with the pace and indicated that they did not have as good an understanding of the materials as they did in the earlier weeks.

Professional Development - NACME provided professional development sessions in 5 of the first 6 weeks. Overall feedback was very positive, averaging above 4 each week. Students found these sessions to be well-organized and the presenters to be well-prepared and informed. They also indicated that they found these sessions of interest, they helped them think of additional PD opportunities, helped prepare for potential internships and motivated them to improve their preparation for a career in Engineering.

Weekly Feedback

Weekly Feedback	Week 1 - June 6-10 (n=51)		Week 2 - June 13-17 (n=39)		Week 3 - June 21-24 (n=53)		Week 4 - June 27-July 1 (n=44)		Week 5 - July 5 - 7 (n=48)		Week 6 - July July 11 -15 (n=37)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
The instructors demonstrated a command of the content	4.55	.757	4.31	.694	4.47	.608	4.16	.776	4.27	.676	4.14	.751
I was interested and engaged in week's classes	4.29	.782	4.15	.779	4.36	.653	3.89	.895	3.96	.944	3.73	.962
I have a good understanding of what was addressed this week.	4.22	.832	3.92	.929	4.15	.770	3.77	.961	3.65	1.082	3.76	1.011
This week's instruction and activities were well-organized	4.06	.968	4.31	.832	4.38	.627	3.95	.806	4.00	.684	3.78	1.084
What I learned this week will help me in other classes I take.	4.57	.855	4.26	.880	4.36	.682	4.09	.676	4.08	.821	3.89	.843
What I learned this week will be helpful in completing my degree.	4.51	.809	4.26	.910	4.42	.719	4.05	.806	3.94	.909	3.86	.887
I will use what I learned this week to complete the course projects	4.59	.804	4.38	.711	4.55	.637	4.41	.693	4.25	.758	4.08	.682
What I learned will better prepare me for potential internships.	4.51	.834	4.36	.707	4.58	.570	4.30	.765	4.25	.838	4.19	.739
I was able to follow and keep up with the pace this past week	4.43	.671	3.92	1.010	4.00	1.074	3.50	1.338	3.46	1.271	3.65	1.184
What I learned this week will be helpful in my future career	4.51	.809	4.33	.737	4.51	.639	4.27	.694	4.33	.808	4.24	.723
Overall Means	4.42	.646	4.22	.639	4.38	.496	4.04	.646	4.02	.669	3.93	.691
Scale (1=SD, 2=D, 3=N, 4=A, 5=SA)												

NACME PD Feedback

NACME PD Feedback	Week 1 - June 6 (n=51)		Week 2 - June 13 (n=39)		Week 3 - June 20 (n=53)		Week 4 - June 27 (no PD)		Week 5 - July 5 (n=48)		Week 6 - July 11 (n=37)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
This past week's NACME PD session was of great interest to me	4.12	.993	4.26	.795	4.21	.840			4.17	.781	4.27	.871
This week's PD helped me think about potential career opportunities	4.12	.973	4.18	.854	4.15	.841			4.12	.733	4.14	.948
This session will help me to explore other courses and PD opportunities.	4.20	.917	4.28	.724	4.08	.805			4.02	.785	4.24	.760
This will help me prepare for potential internship and other PD opportunities	4.37	.824	4.28	.686	4.23	.776			4.19	.704	4.46	.730
This week helped deepen my commitment to finishing my degree	4.10	1.063	3.90	.852	4.11	.870			3.81	.915	4.19	.995
This session helped motivate me for a successful career in engineering	4.31	.836	4.03	.873	4.09	.904			4.08	.846	4.30	.939
The presenter was well-prepared.	4.47	.784	4.49	.601	4.55	.667			4.46	.683	4.51	.651
The presenter was well-informed	4.57	.700	4.46	.643	4.43	.694			4.37	.733	4.51	.768
The presentation was well-organized	4.46	.706	4.41	.595	4.54	.699			4.38	.709	4.42	.692
My participation will improve my preparation for a career in Engineering	4.25	.891	4.23	.706	4.30	.696			4.08	.846	4.32	.852
I look forward to additional sessions like this.	4.31	.948	4.23	.742	4.45	.748			4.19	.842	4.41	.762
Overall Means	4.29	.734	4.24	.508	4.28	.619	NA		4.17	.639	4.34	.704
Scale (1=SD, 2=D, 3=N, 4=A, 5=SA)												

Weekly Feedback by Site

Comparisons among the three sites are summarized in the table below. Each week, statistically significant differences were found in relation to perceived knowledge and ability related to the weekly objectives week with students at the University of Arkansas reporting the most confidence. Also, in the later weeks (week 5 and 6), students at Arkansas reported significantly more positive weekly feedback in comparison to students at Morgan State. More specifically, students from Arkansas reported having a better understanding of what was addressed in weeks 5 and 6. Furthermore, students from Morgan State reported being significantly less engaged in class and had a harder time keeping up with the pace in week 6 in comparison to students from the other sites. Subsequent tables provide a comparison by site for specific weekly objectives.

		Arkansas		Kentucky		Morgan State		
	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)	F	Site Differences
Week 1								
Weekly Feedback	16	4.39 (.53)	15	4.57 (.59)	20	4.34 (.78)	.584	
Objectives	16	4.09 (.58)	15	3.99 (.74)	20	3.53 (.71)	3.60*	UA > MSU
Prof. Dev.	16	4.32 (.53)	15	3.53 (.71)	20	4.34 (.94)	.269	
Week 2								
Weekly Feedback	12	4.38 (.44)	12	4.24 (.97)	15	4.08 (.61)	.598	
Objectives	12	4.06 (.62)	12	3.98 (.44)	15	3.55 (.56)	3.51*	UA > MSU
Prof. Dev.	12	4.17 (.53)	12	4.22 (.43)	15	4.32 (.56)	.275	
Week 3								
Weekly Feedback	15	4.37 (.55)	17	4.57 (.35)	21	4.22 (.52)	2.42	
Objectives	15	4.19 (.72)	17	3.93 (.62)	21	3.13 (.73)	11.56***	UA,UK > MSU
Prof. Dev.	15	4.18 (.67)	17	3.13 (.73)	21	4.41).57)	.765	
Week 4								
Weekly Feedback	15	4.18 (.62)	14	4.19 (.51)	15	3.76 (.73)	2.23	
Objectives	15	3.91 (.55)	14	3.91 (.56)	15	3.03 (.49)	13.51***	UA, UK > MSU
Prof. Dev.		NA		NA		NA		
Week 5								
Weekly Feedback	15	4.13 (.65)	19	4.21 (.64)	14	3.64 (.60)	3.67*	UA > MSU
Objectives	15	3.58 (.51)	19	3.23 (1.02)	14	2.85 (.55)	3.30*	UA > MSU
Prof. Dev.	15	4.25 (.60)	19	4.23 (.59)	14	3.99 (.74)	.748	
Week 6								
Weekly Feedback	16	4.24 (.69)	9	4.01 (.53)	12	3.47 (.58)	5.40**	UA > MSU
Objectives	16	3.71 (.58)	9	3.39 (.79)	12	2.93 (.65)	4.87*	UA > MSU
Prof. Dev.	16	4.42 (.66)	9	4.05 (.76)	12	4.45 (.73)	1.02	
***p<.05, **p<.01, ***p<.001**								

Week 1 Objectives Comparison by Site

(Continued on Page 54)

Week 1 Objectives – comparison by site										
		Arkansas			Kentucky			Morgan State		
	N	Mean	SD	N	Mean	SD	N	Mean	SD	Sig. Differences
Using Python, create, use, and troubleshoot variables	16	4.00	.816	15	4.40	.737	20	3.55	.887	UK > MSU
Read and write Python statements, expressions, conditionals, loops and functions	16	4.00	.816	15	4.33	.724	20	3.65	.813	UK > MSU
Build a basic Python object	16	4.25	.683	15	4.27	.799	20	3.65	.875	
Build a hierarchy of objects	16	3.94	.929	15	3.73	.961	19	3.26	.733	
Distinguish procedural from object-oriented programming	16	4.13	.885	15	3.87	1.125	20	3.50	.761	
Distinguish a class from an instance	16	4.19	.750	15	4.27	.799	20	3.40	.821	UA,UK > MSU
Interpret different types of exceptions	16	4.25	.683	15	4.00	.926	20	3.25	.910	UA,UK > MSU
Create your own exception class	16	4.13	.806	15	3.80	.941	19	3.37	.955	
Define functions using lambda syntax	16	3.94	.929	14	3.86	.770	20	3.40	.940	
Interpret list comprehension notation	16	3.94	.854	15	3.73	.884	20	3.40	.681	
Create lists using list comprehension with for and if statements	16	4.25	.683	15	3.93	.884	20	3.55	.945	
Identify and use basic machine learning (ML) terminology	16	4.25	.683	15	3.87	1.060	20	3.40	.821	UA > MSU
Distinguish between different types of ML models	16	3.94	.772	15	3.53	1.246	20	3.40	.940	

Week 1 Objectives Comparison by Site

Identify ways in which ML biases can have real ethical consequences.	16	4.13	.806	15	4.00	1.134	20	3.60	.821	
Identify where Colab fits in the development environment	16	4.06	.772	15	4.00	1.134	19	3.63	.955	
Edit markdown in a notebook	16	4.06	.772	15	4.13	.915	20	3.95	1.146	
Edit and run code in a notebook	16	4.25	.856	15	4.13	1.060	20	4.05	1.050	
Confidence Scale (1=not at all, 5= A great extent)		4.09			3.99			3.53		

Week 2 Objectives Comparisons by site

(Continued on Page 55)

Week 2 Objectives – Comparisons by site										
	University of Arkansas			University of Kentucky			Morgan State University			
	N	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**Sig. Differences**
Create, analyze and modify a Pandas Series	12	4.00	.739	12	4.00	.426	15	3.47	.743	
Create, analyze and modify a Pandas DataFrames	12	4.00	.739	12	4.00	.426	15	3.33	.816	UA>MSU
Apply filters to Pandas DataFrames	12	3.75	.866	12	3.75	.622	15	3.00	.655	UA,UK > MSU
Group data contained in Pandas DataFrames	12	4.00	.853	12	3.50	.905	15	3.20	.676	UA>MSU
Merge data across multiple Pandas DataFrames	12	4.00	.739	12	3.83	.835	15	3.13	.640	UA>MSU

Week 2 Objectives Comparisons by site

Sort data contained in Pandas DataFrames	12	3.83	.835	12	3.92	.515	15	3.73	.884	
Create and interpret charts and plots to visualize data	12	3.83	.718	12	4.08	.669	15	3.67	.900	
Determine which visualization is approp for a dataset	12	4.25	.622	12	4.33	.651	15	3.67	.900	
Create charts with Matplotlib	12	4.17	.718	12	4.08	.669	15	3.80	.941	
Create charts with seaborn	12	3.67	1.073	11	3.82	.874	15	3.40	.910	
Upload data to Colab	12	4.25	.866	12	4.25	.622	15	4.07	.884	
Download data from public URLs	12	4.42	.515	12	4.08	.793	15	4.13	.915	
Download and obtain data from Kaggle	12	4.33	.651	12	3.92	.900	15	4.13	.915	
Unzip compressed data	12	4.17	.718	12	3.92	.793	15	4.07	1.03	
Identify and calculate statistics for a DataFrame	12	4.17	.718	12	4.25	.622	15	3.33	.816	UA,UK > MSU
Analyze data across DataFrame objects	12	4.00	.853	12	3.92	.669	15	3.40	.828	
Select appropriate visualizations to use in analysis	12	4.17	.718	12	4.00	.603	15	3.60	.910	
Week 2 (continued)		**Arkansas**			**Kentucky**			**Morgan State**		
	N	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**Sig. Differences**
Interpret visualizations to answer questions about a dataset	12	4.08	.669	12	4.17	.389	15	3.73	.594	
Identify and fill in missing data points in a dataset	12	4.00	.603	12	4.08	.669	15	3.33	.617	UA,UK > MSU
Identify and correct broken data points in a dataset	12	4.00	.603	12	3.83	.835	15	3.13	.640	UA,UK > MSU
Acquire and load dataset(s) into Pandas structures	12	4.08	.900	12	3.92	.669	15	3.33	.724	UA > MSU
Inspect data columns descriptions and statistics	12	4.00	.953	12	3.83	.577	15	3.40	.737	
Explore data to understand relationship between features	12	4.17	.835	12	3.92	.515	15	3.47	.640	UA > MSU
Use visualizations to convey trends	12	4.17	.577	12	4.08	.515	15	3.67	.816	
Confidence Scale (1=not at all, 5= A great extent)										

Week 3 Objectives Comparison by Site

(Continued on Page 57)

Week 3 Objectives – comparisons by site	University of Arkansas			University of Kentucky			Morgan State University			
	N	Mean	SD	N	Mean	SD	N	Mean	SD	Sig. Differences
Identify components of a linear regression model	15	4.20	.676	17	4.06	1.088	21	3.33	.913	UA > MSU
Identify how machine learning process applies to linear regression	15	4.27	.884	17	4.18	.728	21	3.33	.658	UA, UK > MSU
Distinguish between parameters and hyperparameters	15	4.07	.799	17	3.82	.883	21	3.38	.740	UA > MSU
Load data packaged with scikit-learn	15	4.27	.799	17	4.29	.772	21	3.67	1.017	
Generate sample data using scikit-learn	15	4.47	.640	17	4.24	.664	21	3.48	.928	UA, UK > MSU
Transform data using scikit-learn	14	4.36	.929	17	3.94	.899	21	3.33	.913	UA > MSU
Train a sample model and make predictions using that model	15	4.07	.961	17	4.18	.728	21	3.10	.768	UA, UK > MSU
Create a data-processing and model-training pipeline	15	4.27	.799	17	3.94	.966	21	3.00	.775	UA, UK > MSU
Create metrics around model performance	15	4.07	.961	17	3.76	1.033	21	2.95	.921	UA, UK > MSU
Visualize predictions returned from a model	15	4.20	.775	17	4.18	.728	21	3.29	1.007	UA, UK > MSU
Train a linear regression model using real data	15	4.13	.834	17	4.18	.728	21	2.86	.854	UA, UK > MSU

Week 3 Objectives Comparisons by site

(Continued on Page 58)

Use Root Mean Square Error (RMSE) to evaluate a linear regression model	15	4.07	.961	17	3.88	1.111	21	2.81	.928	UA, UK > MSU
Visualize features, targets,and predicted targets using a scatter plot	15	4.47	.640	17	3.88	.928	21	3.24	1.091	UA > MSU
Extract quantitative measurements of a regression's model	15	4.13	.990	17	4.00	.866	21	2.86	.854	UA, UK > MSU
Make qualitative judgements of a regression model's predictions	15	4.40	.737	17	3.88	.993	21	3.14	1.014	UA > MSU
Apply polynomial models to regression problems	15	4.20	.941	17	3.88	1.054	21	3.00	.894	UA, UK > MSU
Recognize and correct model overfitting	15	4.07	.799	17	4.00	.866	21	3.14	1.014	UA, UK > MSU
Week 3 (continued)		Arkansas			Kentucky			Morgan State		
	N	Mean	SD	N	Mean	SD	N	Mean	SD	Sig. Differences
Distinguish between types on tensors (scalers, vectors, matrices, cubes, etc.)	15	4.27	.799	17	4.00	1.000	21	3.24	1.091	UA > MSU
Identify key differences between TensorFlow 1 and TensorFlow 2	15	3.73	1.03 3	17	3.47	1.375	21	2.86	1.153	
Perform basic linear algebra operations on tensors using TensorFlow	15	4.07	.884	17	3.76	.903	21	3.24	.944	UA > MSU
Convert tensors to NumPy arrays and Python lists	15	4.33	.724	17	4.18	.728	21	3.52	.981	UA > MSU
Use TensorFlow Estimator API to build a model	15	4.33	.816	17	3.59	1.004	21	3.05	.973	UA > MSU
Adjust model hyperparameters	15	4.13	.990	17	4.00	.935	21	2.86	1.195	UA, UK > MSU

Week 3 Objectives Comparison by Site

Adjust weights and bias in a neural network	15	4.00	.926	17	3.88	1.111	21	3.19	1.078	UA > MSU
Track a basic neural network prediction through hidden layers and activation functions	15	4.07	.961	17	3.65	.996	21	3.00	.894	UA > MSU
Use TensorFlow/Keras API to build a deep neural network	15	4.20	.862	17	3.53	1.007	21	2.81	.981	UA > MSU
Understand the implications of activation function choice	15	4.20	.775	17	3.65	1.057	21	3.05	.921	UA > MSU
Argue the merits (or lack thereof) for a regression model	15	4.27	1.033	17	3.76	1.091	21	2.86	1.014	UA, UK > MSU
Discuss the ethics of a regression model	15	4.40	.737	17	4.12	.857	21	3.24	1.136	UA, UK > MSU
Explore a dataset with minimal guidance	15	4.07	.961	17	4.18	.809	21	3.33	1.278	UK > MSU
Build a regression model and perform hyperparameter tuning	15	4.27	.704	17	4.00	.791	21	2.95	1.024	UA, UK > MSU
Judge the quality of a regression model	15	4.33	.724	16	3.94	.854	21	3.10	.944	UA, UK > MSU

Week 4 Objectives Comparison by Site

(Continued on Page 60)

Week 4 Objectives – Comparison by Site

	University of Arkansas			University of Kentucky			Morgan State University			Sig. Differences
Differentiate between classification and regression	15	4.13	.743	14	4.07	.917	15	3.27	.704	UA,UK > MSU
Interpret accuracy, precision, recall, and F1 scoring to classification models	15	4.27	.799	14	3.71	.825	15	3.33	.900	UA > MSU
Create a logistic regression model for a binary classification	15	3.87	.640	14	4.07	.616	15	3.13	.640	UA, UK > MSU
Interpret a confusion matrix for a binary classification model	15	3.73	.884	14	3.64	1.082	15	3.13	.834	NA
Use grid search to find optimal hyperparameters for a model	15	4.00	.655	14	3.93	.829	15	2.93	.884	UA, UK > MSU
Build a classification model for data with more than two classes	15	3.93	.799	14	4.00	.679	15	3.07	.884	UA, UK > MSU
Use cross-validation to evaluate a model	15	3.93	.704	14	3.93	.616	15	2.93	.799	UA, UK > MSU
Create a model pipeline for training and predicting	15	3.87	.640	14	3.86	.770	15	2.93	.704	UA, UK > MSU
Design, build,train and evaluate a Linear Classifier model in TensorFlow	15	3.93	.704	14	3.93	.616	15	2.93	.884	UA, UK > MSU
Submit predictions to a Kaggle challenge	15	4.47	.743	13	4.23	1.013	15	3.13	.834	UA, UK > MSU
Use effective strategies for feature reduction in image classification	15	3.93	.594	14	3.71	.825	15	2.93	.799	UA, UK > MSU
Perform multiclass image classification using a deep neural network	15	3.87	.743	14	3.71	.914	15	2.93	.884	UA > MSU

Week 4 Objectives Comparison by Site

Prevent overfitting using early stopping and dropout	15	4.27	.799	14	4.00	.784	15	2.93	.884	UA, UK > MSU
Resize, pad and change the orientation of an image	15	4.00	.845	14	4.07	.730	15	3.00	.756	UA, UK > MSU
Load and image with OpenCV	15	4.27	.594	14	4.07	.829	15	3.13	.743	UA, UK > MSU
Modify an image	14	3.93	.829	14	4.07	.730	15	3.07	.704	UA, UK > MSU
Chnage the color encoding of an image	14	3.57	.938	14	4.00	.679	15	3.13	.743	UK > MSU
Implement the process to save the state of a model	14	3.79	.893	14	3.86	.864	15	2.93	.594	UA, UK > MSU
Revise and use a persisted model	15	3.87	.915	14	3.64	1.082	15	2.93	.594	UA > MSU
Use OpenCV to process images and video	15	3.67	.900	14	4.00	.877	14	3.14	.770	UK > MSU
Use a pre-trained model to identify and label objects in each frame of a video	15	3.60	.737	14	4.14	.770	15	2.73	.704	UA, UK > MSU
Judge the classification quality and when to apply predicted labels	15	3.67	.900	14	3.93	.616	15	2.80	.561	UA, UK > MSU
Identify examples of classification models that had unintended, harmful effects	15	3.60	.737	14	3.93	.917	15	3.13	.834	UK > MSU
Distinguish potential causes of bias and harmful errors in classification	15	3.73	.799	14	3.50	1.225	15	3.00	.756	
Discuss ways to mitigate bias	15	3.87	.834	14	3.57	1.399	15	3.00	.845	

Week 5 Objectives Comparison by Site

Week 5 Objectives – Comparison by Site

	University of Arkansas			University of Kentucky			Morgan State University			
	N	Mean	SD	N	Mean	SD	N	Mean	SD	Sig. Differences
Identify the components of a CNN	15	3.80	.561	19	3.53	1.219	14	2.57	.646	UA, UK > MSU
Identify the effect of different filters	15	3.53	.834	19	3.47	1.264	14	3.00	.679	
Use TensorFlow to build a recurrent neural network	15	3.87	.743	19	3.58	1.017	14	2.71	.611	UA, UK > MSU
Feed time series data to a neural network to make sequence predictions	15	3.27	.799	19	3.53	1.073	14	2.93	.829	
Use text processing and feature extraction tools	15	3.40	.828	19	3.21	1.182	14	2.93	.917	
Train NLP models using bag-of-words and sequential representations	15	3.60	.910	19	3.26	1.147	13	2.62	.870	UA > MSU
Understand the fundamental structure of autoencoders	15	3.47	.640	19	3.16	1.463	14	2.86	.663	
Implement an autoencoder for compressing and denoising images	15	3.73	.594	19	3.00	1.528	14	3.00	.679	
Combine multiple models using a wrapper model	15	3.53	.834	18	3.11	1.323	14	2.79	.699	
Familiarity with the PyTorch API	15	3.33	.816	19	2.63	1.461	14	2.57	.852	
Employ the fastai API to implement a CNN	15	3.53	.990	19	2.74	1.327	14	2.57	.852	UA > MSU
Discuss ethical implications of a model that involves medical decisions	15	3.87	.915	19	3.53	1.307	14	3.43	.938	
Create a classification model end-to-end, including parameter tuning and final validation	15	3.60	.632	19	3.26	1.147	14	3.07	.829	

Week 6 Objectives Comparison by Site

Week 6 – Comparison of Objectives by Site

	University of Arkansas			Kentucky			Morgan State			
	N	Mean	SD	N	Mean	SD	N	Mean	SD	Sig. Differ ences
Differentiate clustering from regression classification	16	3.75	.683	9	3.44	1.333	12	2.83	.577	UA > MSU
Manually cluster objects using a tactic similar to the k-means algorithm	16	3.75	.683	9	3.89	.782	12	3.00	.739	UA, UK > MSU
Identify the difference between supervised and unsupervised learning	16	4.06	.772	9	3.67	1.118	12	3.33	.888	
Create a k-means model	16	3.81	.750	9	3.67	1.225	12	3.25	.622	
Interpret the output of a k-means model	16	3.75	.856	9	3.78	.972	12	3.17	.577	
Describe embeddings, why they are used, and how they are trained	16	3.87	.806	9	3.22	1.202	12	3.08	.669	
Implement embedding in practice	16	3.75	.775	9	3.33	1.118	12	3.00	.739	
Create and apply a decision tree algorithm for classification	16	3.75	.775	9	4.00	.866	12	3.08	.669	UK > MSU
Perform ensemble learning using random forests	16	3.75	.856	9	3.89	.782	12	3.08	.793	
Apply limits to depth and split size to reduce overfitting	15	3.93	.799	9	4.00	.707	12	2.92	.793	UA, UK > MSU
Describe the basic concept of KNN	15	3.80	.775	9	4.00	1.323	12	2.83	.835	UA > MSU
Use KNN to solve a classification problem	15	3.80	.775	9	3.89	1.054	12	2.75	.754	UA, UK > MSU
Identify and describe the components of Bayes' Theorem	16	3.63	.957	9	3.33	1.118	12	2.75	1.055	
Predict spam or ham using Bayes	15	3.27	.704	9	2.78	1.787	12	2.75	1.055	
Predict review sentiment (+ or -) using Bayes	16	3.44	.629	9	2.22	1.302	12	2.75	1.055	
Define problems for which support vector machines are a good fot	16	3.69	.873	9	2.78	1.394	12	2.83	.937	
Understand the primary settings used to tune a support vector machine and their tradeoffs	16	3.44	.629	9	3.00	1.500	12	2.75	.866	
Understand the idea of gradient boosting	16	3.75	.775	9	3.33	1.500	11	2.64	.809	UA > MSU
Implement the XGBoost algorithm	16	3.50	.730	9	2.22	1.093	12	2.75	.866	UA >

Recommendations

Consider course prerequisites– Students described challenges in learning programming and were limited in other background skills to do the work in a timely manner. They specifically indicated that having more experience with programming, statistics and linear Algebra would be beneficial.

Course Organization and Expectations – Student focus group comments and ongoing feedback described challenges they had navigating through the course materials and assignments Students from each site described that course expectations and details related to required assignments could be more clearly communicated. They suggested an orientation to the class and syllabus so students understand what is expected. They also suggested using a learning management system (LMS) to organize course activities, materials and assignments. There are helpful organizational features within these LMS such as a dashboard that alert participants (students, TAs and instructors) of the course schedule and when upcoming assignments are due. LMS also offer a way to organize course materials and store completed assignments and feedback that might be helpful to review when working on subsequent tasks.

Course Pace and Modifications -The existing curriculum serves as a guide but some modifications could be made to better serve all students. Two items, focused on student ability to keep up with the pace and have a good understanding what was addressed in class, received the lowest average responses each week. This was especially true as the course progressed and the content became more challenging. Within the course, provide students with opportunities to practice and get feedback or remedial resources to review and develop the skills they may not have had prior to the course. In the focus groups, students also indicated that having some time or days built into the course schedule to catch up and get additional help from TAs or faculty would be valuable.

References

ABET SLOs - https://www.abet.org/accreditation/accreditation-criteria/criteria-for-accrediting-engineering-programs-2018-2019/#GC3

Competencies for Career Readiness – National Association Of Colleges and Employers. https://www.naceweb.org/uploadedfiles/files/2021/resources/nace-career-readiness-competencies-revised-apr-2021.pdf

LAESE – Longitudinal Assessment of Engineering Self-Efficacy - http://aweonline.org/efficacy.html

Mamaril, N.A., Usher. E. L., Li, C, R., Economy, D. R., & Kennedy, M. S. (2016). Measuring Undergraduate Students' Engineering Self-Efficacy: A Validation Study. Journal of Engineering Education, 105 (2), 366-395.

Siwatu, K. O. (2007). Preservice teachers' culturally responsive teaching self-efficacy and outcome expectancy beliefs. Teaching and Teacher Education, 23, 1086-1101.

The Student Attitudes Toward STEM Survey (S-STEM) (Friday Institute for Educational Intervention, 2012; Unfried, Faber, Stanhope, & Wiebe, 2015)

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