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Assessing Instructional Effectiveness and Understanding Factors that Contribute to Student Performance in an Engineering Statistics Course: An Exploratory Study

Dr. James Burns, Western Michigan University

Jim Burns, Ph.D. Assistant Professor Industrial and Entrepreneurial Engineering and Engineering Management Department Bio: Jim Burns holds a Ph.D. in Industrial Engineering from Western Michigan University, and has more than 10 years industry experience in the manufacturing sector in a variety of roles including process engineering, operations management, and technical sales. His area of expertise centers on applying OR/MS and Simulation techniques to Supply Chain & Operations Management problems, and has also conducted research in the areas of Human Factors and Work Design for evaluating time and motion efficiencies of operations. Jim also holds an undergraduate IE degree and a Six Sigma Greenbelt. Prior to joining the faculty at Western Michigan, Jim was an Assistant Professor for the Industrial Engineering Technology program at Purdue Polytechnic Institute.

Mrs. Enas Aref, Western Michigan University

An Engineering professional with 10+ years of experience in manufacturing, inventory control, procurement, import and export. Earned Master's Degree in Project Management, 2015,Keller Graduate School of Management, Wisconsin, USA. Ph.D. Student in Industrial Engineering with research emphasis on Ergonomics and Human Factors, Western Michigan University Instructor and Co-Instructor of several Engineering courses at the Graduate and Undergraduate levels. Research areas: Ergonomics and Human factors, Usability Engineering, Engineering Education, Cyber-Physical Systems

Mr. Mohammad Majd, WESTERN MICHIGAN UNIVERSITY

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Abstract

Multi-disciplinary engineering courses present certain instructional challenges that stem directly from having students from many different programs in one classroom. Challenges include but are not limited to developing meaningful course materials that resonate across the disciplines, finding and applying the appropriate level of rigor for individual topics and for the course as a whole. These difficulties are compounded when the course involves large lecture sections taught by faculty and smaller lab-based sections that are taught by multiple teaching assistants. In such cases it can be difficult to assess the effectiveness both of instruction and student learning.

In this paper, we present the results of an effort to establish a methodology for assessing the quality of instruction and student learning in a multi-disciplinary engineering statistics course at a large, regional university. The introductory statistics course is offered through the Industrial Engineering department and serves approximately 25% of the college's undergraduate student population. The lab-based course is comprised of multiple lecture (2 credit hours, ~100 students) and lab sections (3 contact hours, ~25 students). Lecture sections are taught by faculty and focus on concepts, theory, and application. Lab sections are taught by graduate teaching assistants and focus on reinforcing lecture content and applying concepts with software. The objectives of the work are to: 1) develop a methodology to determine factors that contribute to variation in classroom performance such as students' major and their knowledge of and sentiment toward statistics, and 2) to utilize those factors in developing a model to assess the quality of instruction and student learning across lecture and lab sessions.

Two semesters of performance data are analyzed in development of the regression-based statistical model. Factors explored during model development included major, class level, lab session characteristics (time of day, day of week), lecture section characteristics, lab instructor, measures of student engagement, and student sentiment toward statistics. The final model will serve as a basis for assessing instructional effectiveness as the course undergoes a major redesign between the Fall 2019 and Fall 2020 semesters. tertiary

Introduction

Statistics education is an emerging field that grew out of different disciplines and is currently establishing itself as a unique field of study [1]. In 2010, Hoerl and Snee identified the need to formalize a discipline called "Statistical Engineering" to fill that gap between statistical thinking and statistical tools [2]. Statistical techniques have applications in many areas of our society, so it is reasonable that the subject is taught across many disciplines. Indeed, the educational aspects of statistics have been of interest over the past several decades. Many of these studies have appeared in discipline-specific publications, so educational aspects of statistics can be thought of as studies of those disciplines (e.g., psychology, science education, mathematics education) [3]. The majority of these studies focused on predicting student academic performance [4], identifying the role of motivation, personality and other psychosocial factors in the performance of students [5]. Several other studies were conducted to assess the effectiveness of different learning environments (i.e classroom instruction vs. online courses), and blended learning [6] [1], there were contradicting findings considering student performances. Other studies were conducted to assess differences in various content *delivery techniques* in engineering classrooms in general, and for engineering statistics in particular [3] [7]. These studies provide valuable guidance for instructors teaching statistics in an engineering context. However, it is also necessary for educators to understand the factors that affect student learning in their own particular courses. Such factors can be described as either institutional-based or student-based. Examples of institutional factors that were studies in previous research endeavors were: campus environment, student population size, campus facilities, institutional type and course format, student support services and campus activities [8]. In this research, institutional factors focuses on those factors that stem from the nature of the course itself (the semester, day, or time that a course is offered), or factors associated with instructors teaching the course (experience and background). Student-based factors could stem from a student's major, class standing, motivation and work ethic outside of the classroom, interest in the subject, and a host of other factors.

Although the notion of a comprehensive student assessment program that accounts for all possible institutional and student-level factors is compelling, it is an extraordinarily difficult goal to achieve in the short-run and will likely need to be modified over time. Therefore, a rational approach for educators to understand the factors that are at play in their classrooms is to build a methodology for factor identification and assessment that can be updated continually. While several studies focused on predicting student academic performance based on different student and institutional factors [4] [9], the objective of this study is to document the initial steps of developing a statistical methodology that can identify such factors and is capable of assessing important institutional-level factors for an undergraduate engineering statistics course. For the authors, the work done for the study provides a framework and grounding for continued efforts that will accelerate in the Fall 2020 semester as the course undergoes a major redesign. For the engineering education community, the study highlights important considerations for curriculum assessment using statistical techniques that are commonly applied in engineering, including some limitations of the methods.

This paper is organized into five sections describing the following: the engineering statistics course being evaluated, the data used in the modeling, the statistical methods used in the modeling, the results of the analysis, and finally the findings and implications of the work for the authors and the engineering education community.

Course description

This study focuses on an introductory statistics course that is offered through the Industrial Engineering department at a large public university. This course serves approximately 25% of the college's undergraduate student population. The course is structured in a lecture-lab format, with two one-hour lecture meetings per week and one three-hour lab meeting per week. Lecture sections are taught in a lecture hall (~100 students) by faculty and focus on concepts, theories, and some applications. Lab sections are taught in classrooms (~25 students) primarily by graduate teaching assistants (TA) and focus on reinforcing concepts and applying concepts with software. These classrooms are equipped with desktop computers which provide students with access to Minitab software. This course is offered in both Fall and Summer semesters. Due to the typically large size of enrollment in Fall semester (200+ students), lecture sections are offered twice per week at two different times: morning lecture (AM) and afternoon lecture (PM). In Fall semester, nine lab sections are offered Monday through Thursday. Lab sections are scheduled at different times of day (Morning, Afternoon and Evening). Upon enrolling in the class, each student registers for a lab section that works with their schedule. Students are asked to attend only the lab section they are enrolled in.

The course primarily serves students from the Paper (PAP), Chemical (CHM), Industrial (IE), Civil (CIV), Electrical and Computer Engineering programs (ECE), and Technology programs majors (TECH) including students from Design, Manufacturing and Engineering Management. The course is cross listed with a course from the university's statistics department, and occasionally students from departments outside the engineering college are enrolled in the course. An enrollment distribution summary is provided in Table 1.

The nine lab sections for the course are taught primarily by TAs from the master's and doctoral programs of the Industrial Engineering (IE) Department. The majority of TAs serving the course have prior experience teaching in the IE department. Eleven different lab instructors were involved with the course over the study period, seven of which were doctoral students, three were master's

Table 1: Student enrollment per semester and lecture

Semester	Lecture Section	Class					Total
		Freshman	Sophomore	Junior	Senior	Graduate	
Fall 2018	AM	1	36	36	30	0	103
	PM	4	33	34	16	3	90
Fall 2019	AM	3	38	49	20	0	110
	PM	1	29	40	21	0	91

students, and one was the faculty responsible for the course. Four of the eleven TAs had taught a lab for the course at least twice before.

Lab assignments cover the content that was taught in the respective lab meeting. While completing lab assignments, students have access to the course textbook, lecture notes, lab notes, and can have their questions answered by the TA. As a result, lab assignment scores are usually very high. Homework assignments cover content from recent lectures and labs and are done individually. Homework scores are usually significantly lower than lab scores overall. TAs are responsible for grading both the homework and the lab assignments for students in their lab. Homework and lab assignments are each worth 22.5% of final grade. An engagement score, which is worth 5% of the final grade is assigned to each student by the TA. The engagement score is a subjective score that is assigned by considering 1) student attentiveness and participation in lab, 2) timely completion of work, and 3) lab attendance.

The most objective evaluation component of the course are the three exams, which are administered during lectures and comprise 50% of the overall course grade. Exams assess students' conceptual understanding of the material, their ability to choose and apply appropriate course concepts to straightforward questions, and their ability to apply multiple concepts to a larger problem. Students have access to self-constructed reference sheets and statistical tables during exams. Software is not used during exams. Exams are not returned to students to keep and exam procedures are tightly controlled, minimizing the likelihood of cheating. Exam scores are weighted in the final grade calculation, with the lowest exam score accounting for a lower percentage of the final grade, but a raw average was used as part of the data.

In order to evaluate the sentiment of students toward statistics, a survey was conducted at the beginning of each semester. The survey consisted of five questions; all were answered on a five-point Likert scale where the responses range from "Strongly Disagree" to " Strongly Agree". The survey questions are:
1) My view the field of statistics and its use in society as a positive one
2) I expect to use statistical techniques in my career
3) I believe statistics is important to experimentation and the scientific (or engineering) method
4) Statistics improves the quality of the information I receive on a daily basis
5) I am confident that I will do well in this course.

Data description

The data analyzed in this study was collected from all sections of the Fall 2018 and Fall 2019 semesters and included records for all students who completed the course. Data was collected through the university's Learning Management System (LMS). A record of all grades and student-level information of interest were compiled. The final grade for the course is calculated using individual assessment items from the following categories: Lab assignments, Homework assignments, Engagement, and Exams. All of these grade components were used as exploratory factors and variables in different model development iterations, with the final dependent variable being the raw average of the three exams (EXAMAVE).

The emphasis of the analysis is to identify factors that are in some way under our control, while accounting for factors that are largely outside our control which are also likely to confound our ability to identify ways to improve the course. A sampling of factors available for the dataset is presented in Table 2. Of these factors, some are fully under our control, others are partially under our control, and some are entirely out of our control from an instructional effectiveness standpoint. Factors considered to be under our control are semester (SEM), lecture (LEC), and session (SESSION), as these factors relate to the overall performance of the instructor(s) as a whole (assuming the nature of students in the course is consistent from year to year). Factors that are partially under our control are TA, experience (TAEXP), and degree (TADEG). While it is not always possible for the faculty to select each TA, some control is possible, and it is also attainable to improve the training and mentoring of TAs. Factors considered to be outside our control include major (MAJ) and lab attendance (LABATT), average lab score (LABSCORE), and homework score (HWSCORE), because they relate directly to student choices. Nuisance

Table 2: Relevant Factors

ID	Description
SEM	Semester (19: Fall 2019, 18: Fall 2018)
LEC	Lecture section (AM: Morning section, PM: Afternoon section)
SESSION[1]	Combined SEM and LEC factor (19AM, 19PM, 18AM, 18PM)
MAJ	Student Major (CHM, CIV, ECE, IE, PAP, TECH)
TA	Lab instructors (1…11)
TAEXP	Experience of lab instructor (1: Previously taught a lab 2 or more times, 0: otherwise)
TADEG	Instructor education (1: PhD or Doctoral student, 0: otherwise)
LAB	Lab code, identifying the day/time a lab occurs (1...9)
LABDAY	Day of the week that lab is held (1: Monday, 2: Tuesday, ... 4: Thursday)
LABTIME	Time of the day lab is held (1: Morning, 2: Afternoon, 3: Evening)
LABATT[2]	Attendance of students divided by the total number of labs. Reported as percentage.
LABSCORE[2]	Average of all lab assignment scores. Reported as percentage.
HWSCORE[2]	Average homework score for all assignments. Reported as percentage.
ENGAGESCORE[2]	Subjective score of a student's engagement in the course. Reported as a percentage.

[1]Developed as a replacement to SEM + LEC + their interaction. [2]Indicates continuous predictor.

factors include lab section (LAB), day of lab section offering (LABDAY), and time of day of lab section offering (LABTIME). The final dataset used in the analysis was compiled after the initial exploratory process and after filtering were done to remove records that would unreasonably skew the analysis. The final inclusionary criteria for the study were:

1. Students completing at least two exams out of three.
2. Students attending at least six lab sessions out of twelve.
3. Students from the primary engineering majors the course serves.

The final dataset was comprised of 394 students. Descriptive statistics and illustration of student distributions by major across the labs and lecture sections are shown in Table 1, Figure 1, and Appendix A.

Data Analysis

The analysis activities of the study included an initial mixed methods analysis used to understand the nature of the data collected and regression techniques used to determine the significance and importance of factors. Microsoft Excel and Minitab software were used for the initial data analysis and Minitab's General Linear Modeling function was used to develop and test several regression models. The regression models included categorical factors and continuous factors that were used as student-level covariates in the analysis (Figure 2). The goal of the initial analysis was to identify

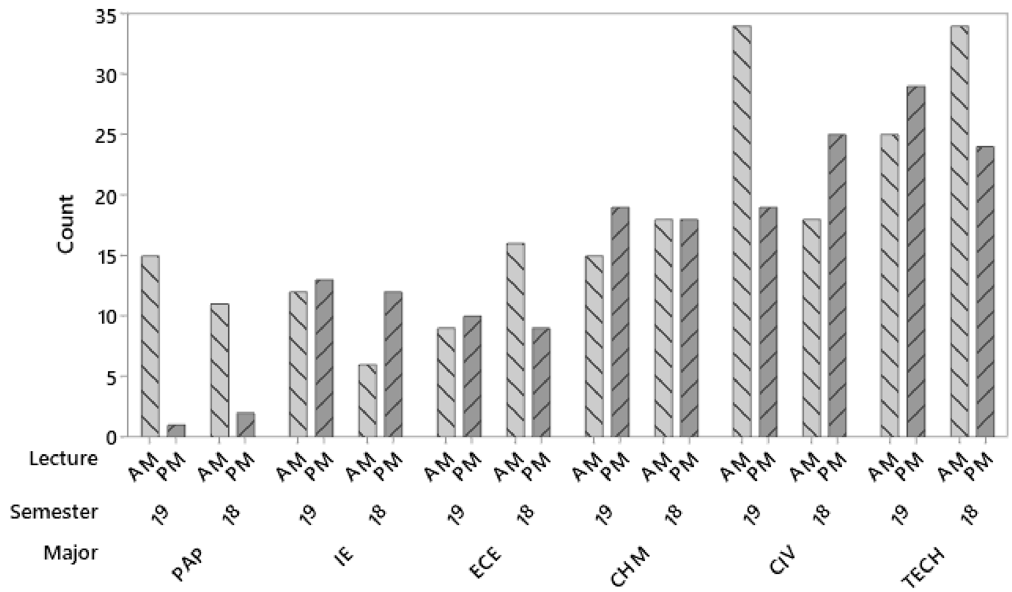

Figure 1: Student Major Distribution per Lecture and Semester

factors and factor combinations that would have potential to serve as explanatory variables in the regression models. Factors were evaluated according to 1) their suitability in explaining variance in a way that improves our ability to assess instructional effectiveness, 2) their statistical significance, 3) their individual R-Squared (RSQ) and/or overall contribution to the RSQ of a multiple regression model (Type-III semi-partial correlation), and 4) the validity of the model

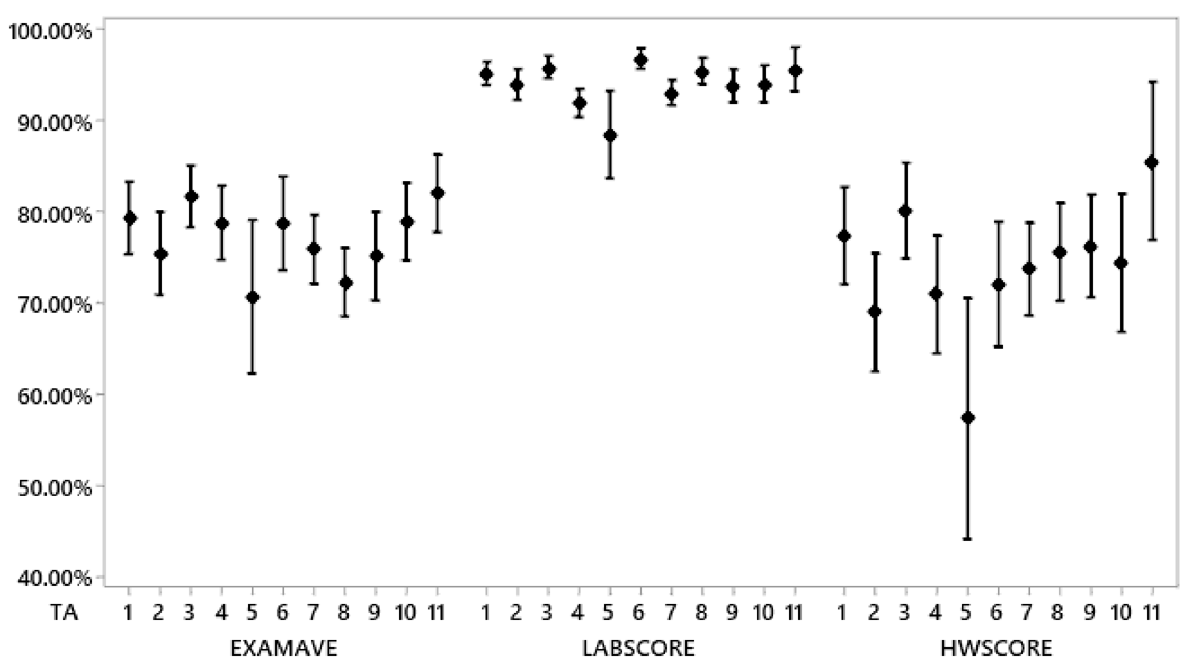

Figure 2: Mean and 95% CI for Dependent Variable EXAMAVE and Covariates LABSCORE, HWSCORE

produced by the factor or factor combinations. For exploratory portions of the analysis, models were developed using both Type-III and Type-I (sequential) Sums of Squares (SS). Although no meaningful differences were observed due to how SS was calculated, the final model described was developed with Type-I SS.

Table 3: Single Factor Model Results

Factor	RSQ	*p*-value
SEM	0.00	0.80
LEC	0.02	0.00
SESSION	0.04	0.00
MAJ	0.15	0.00
TA	0.05	0.02
TAEXP	0.01	0.06
TADEG	0.01	0.20
LAB	0.05	0.01
LABDAY	0.01	0.16
LABTIME	0.01	0.15
LABATT	0.12	0.00
LABSCORE	0.26	0.00
HWSCORE	0.25	0.00
ENGAGESCORE	0.06	0.00

Results

Table 3 presents a summary of selected factors, their significance levels, and individual statistical relationships with the dependent variable of interest (raw average of the three exam scores, EXAMAVE) and Table 4 presents a summary of models combining multiple factors, including the final model. The highest RSQ values for individual models were obtained by LABSCORE, HWSCORE, and MAJ, all of which were included in the final model. LAB and TA had similar explanatory power, but TA had greater contribution to RSQ in the final model.

Many factors that would seem to have contributed to differences in performance did not turn out to have meaningful relationships or explanatory value in the models (e.g., survey questions), while others that were known to influence performance (e.g., MAJ) were useful. Ultimately, the authors were interested to observe if there were significant differences among the teaching assistants, lecture sections (to identify differences in student performance that could be attributed to the same faculty teaching at different times of the day), and lab sections. The models generated and the

Table 4: Combined Factor Model Results

	Model											
	Final		1	2	3	4	5	6	7	8	9	10
RSQ:	0.49		0.50	0.49	0.48	0.50	0.47	0.47	0.35	0.34	0.23	0.23
Factor	*SPC*	*p*-value[1]										
SESSION	2.59	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MAJ	6.96	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LAB					0.20	0.14					0.02	
TA	2.27	0.11	0.01	0.12						0.08		0.17
LABSCORE	9.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00				
HWSCORE	6.86	0.00	0.00	0.00	0.00	0.00	0.00	0.00				
ENGAGESCORE			0.98	0.92		0.75		0.64				
TAEXP					0.70		0.44		0.04			
LABATT			0.01			0.09	0.14		0.00			

[1]A p-value of 0.00 indicates p<0.001

relevant statistical analysis explained that apparent differences do not necessarily reflect true differences.

The final model resulted in an RSQ of 49.09% and included SESSION, MAJ, LABSCORE, HWSCORE, and TA. The Type-III semi-partial correlations (SPC) shown for the final model indicate the unique variance explained by adding the factor to the model. The final model contains student-level and institutional-level factors and includes factors of interest to the authors. The factor TA is not significant at 11% and all other factors are significant at 5%. An overall analysis of the final model indicates it is strong in some ways and marginal in others. The Variance Inflation Factor (VIF) for SESSION is moderately high, although not alarmingly so. Residuals are normally distributed and present equal variance within the factor levels. Appendix B contains a full model summary and regression coefficients for the final model.

Table 5: Tukey Comparisons

SESSION	N	Raw Mean	Adjusted Mean	Grouping	
19AM	104	81.09%	81.46%	A	
18AM	100	77.87%	79.12%	A	B
18PM	85	76.79%	77.47%	A	B
19PM	85	73.57%	75.46%		B
TA	**N**	**Raw Mean**	**Adjusted Mean**	**Grouping**	
5	17	70.69%	81.81%	A	B
4	40	78.77%	81.37%	A	
10	42	78.90%	79.96%	A	B
11	21	82.01%	79.56%	A	B
2	42	75.44%	78.87%	A	B
3	45	81.66%	78.58%	A	B
1	41	79.30%	78.16%	A	B
7	41	75.87%	77.67%	A	B
6	23	78.71%	77.00%	A	B
9	40	75.14%	76.90%	A	B
8	22	72.29%	72.27%		B
MAJ	**N**	**Raw Mean**	**Adjusted Mean**	**Grouping**	
ECE	41	82.70%	81.41%	A	
CHM	68	82.62%	80.71%	A	
IE	42	80.53%	80.01%	A	
PAP	29	81.41%	79.30%	A	
CIV	91	77.44%	76.78%	A	
TECH	103	69.92%	72.06%		B

* Means that do not share a letter are different.

Tukey post-hoc comparisons were performed using 5% significance for the factors SESSION, TA, and MAJ, and the results are summarized in Table 5. The table presents raw means for each factor level in addition to means adjusted for continuous predictors (covariates). For SESSION, the afternoon lecture session of the fall 2019 semester (19PM) was different than the other sections. For TA, the lone difference was between TA 4 and TA 8. For MAJ, it was found that TECH was different than other majors. An interpretation of the meaning of these differences and the final model itself is contained in the next section.

Discussion & Implications

Our goals for this study were to develop a methodology to determine factors that contribute to variation in classroom performance such a student's major and their knowledge of and sentiment toward statistics, and to utilize those factors in developing a model to assess the quality of instruction and student learning across lecture and lab sessions. For our course, we have identified multiple factors that have influenced learning (as measured by exam scores), including majors, lecture sections, and lab sections (as measured by the factor, TA). Factors that are not associated with learning include TA experience and course engagement (as we have defined them for this study). The statistical model and the modeling procedures we have used provide insight into the past two semesters and serve as a basis for us to assess instructional quality in future sections of the course. In this section we will highlight some findings that provide insight into the current state of our course and comment on aspects of what we have done that are noteworthy for the engineering education community.

A fundamental concern the authors have is ensuring consistency of instruction across lecture and lab sections. The variation associated with student-level factors within any given lecture and lab section makes single-factor comparisons problematic, so multi-variate analysis is needed. Our hope was that after accounting for some of these factors we would find no statistical differences between lecture or lab sessions. The results in this regard are mixed. There are detectable differences between two of the four lecture sections and two of the TAs. Other findings of interest for us are more nuanced. For example, it was surprising that there were no differences between the engineering majors (only between engineering and technology). We have noticed through the years that ECE majors have tended to perform best on average, and we assumed this would show as a statistical difference in the analysis. These findings alone reinforce the importance of controlling for key factors when assessing instructional quality.

It is encouraging to see a lack of widespread differences across the lab instructors. Although we assume there are differences between the TAs in terms of their knowledge of statistics (driven by interest and area of specialization), it is important to ensure these differences do not impact student learning. The absence of widespread statistically significant differences may suggest that the course is well-organized enough to mitigate difference any differences between the TAs, and therefore differences between lab sections. It is of course natural for lab instructors to be curious about how their performance in teaching students the fundamentals of statistics compare to their peers or to an expected standard. The results show that it would be both unwise and unfair to draw conclusions based strictly on average performance without accounting for other factors. For example, consider the large difference in the raw average observed between TA 5 and TA 11 that is not statistically significant. The difference in raw means is apparently due to there being many students from the technology programs in TA 5's lab section (Figure 3). When the raw scores are adjusted for other factors in the statistical model, we see that TA 5's effectiveness is actually much stronger. While the fact that the distribution of majors is different can be observed without a statistical model, drawing conclusions about the effectiveness of any TA without first accounting for the influence of other factors would be pure guesswork. This is exactly the kind of information we wanted to obtain from the model.

For the engineering education community, we believe this study highlights that the same statistical methods used to assess student learning can be applied to assess aspects of instructional effectiveness in large courses. These methods also display the importance of performing investigations to determine the factors that are influencing outcomes rather than relying on assumptions or intuition. For those teaching statistics in the engineering field, where the instructional emphasis is often on designing and evaluating experiments and probability, this study

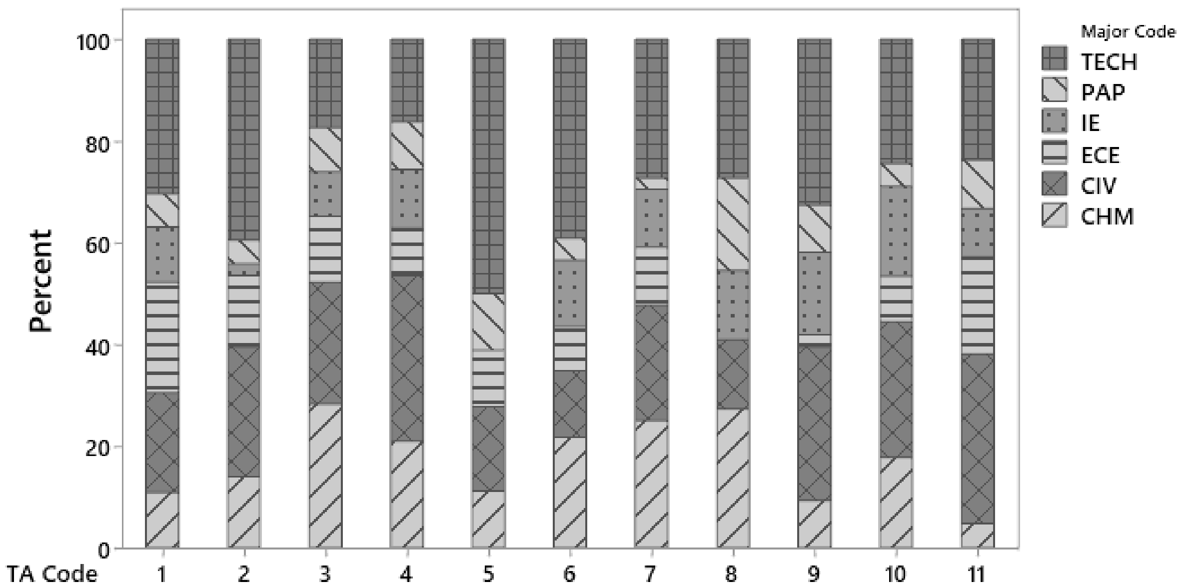

Figure 3: Class distribution per lab session (TA)

underscores an opportunity to show students how the same methods used to investigate technical problems can be applied to people-centered issues.

Moving forward, we have identified aspects of this method we believe must be addressed. First and foremost, the need to obtain objective measures of student performance outside of the in-class exams should be addressed. Homework and lab scores provide some measure of objectivity, but their ability to truly assess knowledge is limited because homework is done entirely outside of class and the labs assessments are really meant to be more of a learning activity than they are an assessment. Developing standardized questions that can be given during short quizzes will provide covariates that contain pre- and post-lesson information. These standardized questions will include questions from the past two semesters so that we can continue to analyze some of the data from this study. Development of new questions is underway and will leverage already validated test instruments for statistics [4].

It is also appropriate for us to explore other student-level factors. We know the math backgrounds of students vary in terms of students who have previously taken a statistics class, in terms of the language with which students received their primary math instruction, and in terms of the number of math courses taken. We strongly suspect these variations influence performance, and we will be collecting information about these factors in the future. There is also a need to more accurately gauge students' attitude toward statistics than how we are measuring it during the initial course survey. In its current format, the course does not seem to engage students to the extent we would like [5] and believe that a student's attitude toward the subject might correlate with performance.

Lastly, we intend on exploring more advanced statistical techniques in order to better understand the significance of individual factors. Multi-level molding techniques such as Hierarchical Linear Modeling (HLM) will likely provide more accurate estimates of the statistical errors that are used to detect differences within factors and allow for better estimation and interpretation of interactions. For example, there may be interactions between lab sections or TAs and certain majors (the nature of this dataset precluded us from exploring most of the nested/multi-level models we were interested). The use of HLM techniques is being explored with the current dataset.

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Appendix A

				EXAMAVE		HWSCORE		LABSCORE	
LAB			N	Mean	StDev	Mean	StDev	Mean	StDev
1			41	77.23%	13.15%	74.25%	21.48%	94.07%	6.39%
2			39	76.55%	13.20%	75.07%	18.76%	92.59%	4.79%
3			42	73.87%	9.57%	73.88%	13.08%	94.77%	3.35%
4			46	76.24%	14.56%	68.68%	19.73%	94.80%	5.63%
5			42	79.83%	11.79%	73.94%	16.95%	93.38%	4.36%
6			39	78.63%	12.03%	74.60%	22.77%	93.65%	5.12%
7			44	81.52%	10.65%	82.33%	16.53%	96.02%	4.28%
8			47	80.89%	14.17%	80.21%	17.60%	94.99%	4.94%
9			34	71.50%	15.08%	63.53%	23.48%	90.99%	7.67%
				EXAMAVE		HWSCORE		LABSCORE	
MAJ			N	Mean	StDev	Mean	StDev	Mean	StDev
CHM			68	82.62%	10.94%	80.35%	16.04%	95.17%	4.35%
CIV			91	77.44%	14.01%	74.82%	21.40%	93.70%	6.09%
ECE			41	82.70%	10.32%	72.93%	20.93%	95.23%	2.67%
IE			42	80.53%	12.59%	78.91%	12.60%	93.99%	5.28%
PAP			29	81.41%	10.54%	75.04%	20.01%	94.60%	5.87%
TECH			103	69.92%	11.66%	68.43%	20.09%	92.94%	5.78%
				EXAMAVE		HWSCORE		LABSCORE	
TA			N	Mean	StDev	Mean	StDev	Mean	StDev
1			41	79.30%	12.57%	77.38%	16.79%	95.10%	4.02%
2			42	75.44%	14.60%	69.00%	20.68%	93.87%	5.38%
3			45	81.66%	11.25%	80.09%	17.44%	95.77%	4.08%
4			40	78.77%	12.69%	70.97%	20.20%	91.86%	4.82%
5			17	70.69%	16.30%	57.40%	25.60%	88.42%	9.24%
6			23	78.71%	11.88%	72.07%	15.77%	96.72%	2.64%
7			41	75.87%	11.97%	73.70%	16.09%	92.99%	4.42%
8			22	72.29%	8.45%	75.60%	12.07%	95.36%	3.27%
9			40	75.14%	15.10%	76.23%	17.47%	93.75%	5.57%
10			42	78.90%	13.54%	74.41%	24.19%	93.95%	6.48%
11			21	82.01%	9.34%	85.51%	19.00%	95.54%	5.32%
				EXAMAVE		HWSCORE		LABSCORE	
SESSION	SEM	LEC	N	Mean	StDev	Mean	StDev	Mean	StDev
19AM	19	AM	104	81.09%	12.00%	76.43%	16.69%	94.70%	4.70%
19PM	19	PM	85	73.57%	12.59%	73.60%	17.14%	94.28%	4.19%
18AM	18	AM	100	77.87%	12.80%	71.88%	23.64%	93.76%	5.46%
18PM	18	PM	85	76.79%	13.80%	75.39%	19.53%	93.27%	6.80%

Appendix B

Source	DF	Seq SS	Seq MS	F-Value	P-Value
MAJ	5	0.96	0.19	21.21	0.00
LABSCORE	1	1.32	1.32	144.59	0.00
HWSCORE	1	0.47	0.47	51.58	0.00
SESSION	3	0.20	0.07	7.46	0.00
TA	10	0.14	0.01	1.57	0.11
Error	353	3.21	0.01	166.92	0.06
Total	373	6.31			

S	R-sq	R-sq(adj)	R-sq(pred)
0.0954	49.09%	46.20%	42.74%

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	-0.18	0.10	-1.85	0.07	
MAJ					
CHM	0.02	0.01	2.06	0.04	2.36
CIV	-0.02	0.01	-1.57	0.12	2.22
ECE	0.03	0.01	2.21	0.03	2.77
IE	0.02	0.01	1.21	0.23	2.72
PAP	0.01	0.02	0.57	0.57	3.37
LABSCORE	0.86	0.11	7.90	0.00	1.39
HWSCORE	0.20	0.03	6.90	0.00	1.37
SESSION					
18AM	0.01	0.02	0.47	0.64	5.11
18PM	-0.01	0.02	-0.54	0.59	5.27
19AM	0.03	0.02	1.92	0.06	5.33
TA					
1	-0.00	0.02	-0.10	0.92	2.87
2	0.00	0.02	0.24	0.81	2.92
3	0.00	0.01	0.14	0.89	1.42
4	0.03	0.02	1.43	0.15	2.87
5	0.03	0.03	1.29	0.20	2.96
6	-0.01	0.02	-0.57	0.57	2.82
7	-0.01	0.02	-0.34	0.73	2.87
8	-0.06	0.02	-2.49	0.01	2.86
9	-0.01	0.02	-0.71	0.48	2.85
10	0.02	0.02	0.76	0.45	2.91