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Redesigning a multi-disciplinary measurement lab and statistics course: An approach for navigating competing priorities

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Abstract

The design of an engineering course is challenged by the need to balance breadth vs depth while meeting ABET criteria, preparing students for the Fundamentals of Engineering (FE) exam, and maintaining within-institution course equivalencies. These difficulties are further exacerbated for the topics of measurement (including data acquisition) and data analysis (including statistics) because many universities package these vast topics into one course. In this paper, we describe the process of redesigning a data analysis and measurement course so that it better meets its program- and college-level goals. We gathered feedback about the course from students, faculty, and employers, and we analyzed the role of this course with respect to ABET criteria, the FE exam, and its relationship to similar courses in the college. We then used a curricular-priorities framework to organize the course's learning objectives into three categories—enduring understanding, important to know and do, and worth being familiar with—and employed a backward-design approach to creating the corresponding assessments and activities. For the classroom activities, we incorporated a flipped-classroom design and interwove the measurement and statistics topics throughout the curriculum, rather than relying on the more common approach of sequentially addressing these topics. The resulting course curriculum is being classroom tested in Spring 2023.

Introduction

Measurement and data analysis are essential topics in engineering education, as they provide students with the skills needed to acquire, process, and interpret data. However, designing or modifying a course on these topics can be challenging due to competing priorities such as meeting learning objectives related to breadth vs. depth, ABET criteria, preparing students for the Fundamentals of Engineering (FE) exam, and maintaining within-institution course equivalencies. This work describes an approach to navigating these competing priorities when redesigning an upper-division measurements and statistics course hereafter referred to as Data Analysis.

Data Analysis is offered by a small (<150 students), relatively new (created in 2013), degree-granting program at a large, research-focused institution in the Rocky Mountain Region of the United States. The program, called the Integrated Design Engineering (IDE) Program, emphasizes design and hands-on experiences in their courses, and students choose a disciplinary emphasis (mechanical, aerospace, environmental engineering, etc.) and a concentration (business, space, engineering management, etc.) as part of this flexible degree. Data Analysis is a four-credit-hour course that combines lecture and lab time throughout a 16-week semester, and the course is required for certain emphases, including the mechanical engineering emphasis, which is the most popular disciplinary emphasis among IDE students.

Because mechanical engineering is the most popular emphasis, the learning objectives of IDE's Data Analysis course were based on the Mechanical Engineering department's version of Data Analysis, such that the two courses would be listed as equivalent in the course catalog, and students in both units could take either course. The Data Analysis course in

Mechanical Engineering stemmed from the consolidation of three, two-credit-hour courses: Experimental Design and Data Analysis, Measurements Lab I, and Measurements Lab II. This consolidation has pedagogical advantages, such as pairing the introduction of a statistical analysis method with its immediate application to a laboratory experiment, but it also has disadvantages, namely students have less class time to learn the fundamentals of two vast fields of study—statistics and measurement.

Initially, the content of the IDE's Data Analysis course was organized in series, focusing on measurement topics first and statistical concepts second. This sequential model had two major disadvantages. First, because the measurement and data acquisition content was concentrated at the start of the semester, many students struggled to remember what they "learned" in the first part of the class when they completed their culminating project later in the semester, in which they designed their own experiment and then collected and analyzed their own data. This phenomenon illustrated that students would benefit from more deliberate, distributed practice with measurement and data acquisition [1]. Second, the measurement and data acquisition activities were much more hands-on than the statistics curriculum, creating very different energy and engagement in the class throughout the semester. We wanted to modify the course to address these two concerns but decided to take a more holistic approach to the redesign.

This paper outlines our comprehensive approach to redesigning Data Analysis. We not only consider changes to the assessments and activities of the class, but we also re-evaluate the learning objectives in the context of program and college level goals and students' professional careers. We utilize a curricular priority framework to organize the course's learning objectives into three categories: enduring understanding, important to know and do, and worth being familiar with [2]. Then, we used a backward-design approach to create corresponding assessments and activities [2]. Our approach utilizes research-based practices for curriculum design and exemplifies a framework for other educators who may be facing similar challenges in redesigning a course, especially a measurement and statistics course.

Background

Course Redesign Framework

Backward design is a framework for curriculum development that begins with the end in mind. The process starts by identifying the desired outcomes or learning objectives for the course and then working backward to create assessments and activities that align with those objectives. This approach ensures that the course is designed with the ultimate goal of student learning in mind and that all aspects of the course are aligned with the needs of the students, the curriculum, and the stakeholders [2, 3].

In the context of redesigning our Data Analysis course, we used the backward design framework to identify the most important learning objectives for the course, and we then created the assessments and activities that aligned with those objectives. This approach allowed us to design with the end in mind while ensuring that the course met the requirements of ABET criteria, the FE exam preparation, and within-institution course equivalencies.

The use of the backward design framework for curriculum design in engineering has precedence. For example, Mohammed et al. [4] used backward design for designing a quality management and analytics course, and Lulay [5] and Dillon [6] led teams that leveraged the framework when creating new modules for a materials and a mechanical engineering laboratory, respectively. Sutterer [7] used a variation of backward design to modify a mechanics of materials course, and Villalta-Cerdas and Yildiz [8] used it for designing an engineering technology bridge course. When considering other laboratory contexts, backward design has been used for chemistry laboratory curriculum and laboratory research experiences for undergraduates [9, 10].

Curricular Priorities Framework

The curricular priorities framework presented by Wiggins and McTighe [2] outlines three categories of learning goals: enduring understanding, important to know and do, and worth being familiar with.

Enduring understanding refers to the big ideas or concepts that are central to a particular subject area and that students should understand deeply over time. These are the core ideas that will have lasting significance for students and that they can apply in various contexts.

Important to know and do refers to the skills, knowledge, and processes that are necessary for students to be able to use and apply the enduring understandings. These are the most essential and practical elements of a subject that students need to know and be able to do to be successful in that field.

Worth being familiar with refers to supplementary information and perspectives that students should be aware of, but that are not as essential as the enduring understandings and important to know and do elements. This category includes background information and alternative viewpoints that can enrich students' understanding and provide a more complete picture of a subject.

By using this framework, educators can prioritize the content they want students to learn and ensure that they are teaching what is most important and meaningful to students.

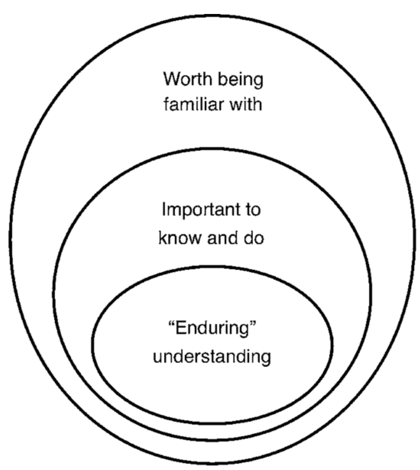

Figure 1. We sorted our learning objectives into three categories of curricular priorities [2].

Contextual Influences on Learning Objectives

When redesigning this measurement and design course, we identified four priorities that influenced our decisions about the learning objectives of the course: 1) balancing the breadth vs. depth of the content in the limited time of the semester, 2) meeting the ABET student outcomes related to this course, 3) preparing students for the NCEES Fundamental of Engineering (FE) exam, and 4) ensuring that the course continues to serve as an equivalent course to similar courses in other departments in the college.

This course introduces students to two vast fields of study, with multiple courses for each field at many universities. For example, when considering only the field of statistics, the Engineering Management Program at CU Boulder dedicates entire classes to two-group comparisons, experimental design and one-way ANOVAs, two- and three-way ANOVAs, and regression and data mining. Thus, in a four-credit-hour course, it is challenging to determine what content should be introduced and to what depth the content should be explored. Based on the experience of one of the authors teaching this course in the past, the students leave with a superficial understanding of the concepts in this course when trying to cover too much content. However, with this Data Analysis course being the only measurement and statistics course that most students take before graduation, it necessarily must explore a wide range of topics. We had to make difficult choices about what topics to emphasize to gain depth in those areas, and ABET outcomes, FE exam prep, and other courses in the college influenced our decisions.

As with many of the courses within the IDE Program's curriculum portfolio, this data analysis course aligned with many ABET Criterion 3 student outcomes, but the program relied heavily on it for certain outcomes. For example, this course contributes to Student Outcomes 1, 3-7, but it plays a lead role in developing students' "ability to develop and conduct appropriate experimentation, analyze and interpret data, and use engineering judgment to draw conclusions" [11]. It is critical for the program's ABET accreditation that our course continues to play a role—sometimes a lead role—in program-level education objectives.

Another program-level objective is to prepare students to successfully pass the NCEES Fundamentals of Engineering exam, which includes a section on statistics that covers the following topics: estimation, expected value and expected error in decision making, sample distributions and sizes (e.g., significance, hypothesis testing, non-normal distributions), and goodness of fit, including correlation coefficient, standard errors, and R^2 [12]. The purpose of this exam is to test engineers' overall competency across core areas of an undergraduate degree in a given engineering discipline. IDE students are required to take the FE exam prior to graduation, and they are encouraged to take the "Other Disciplines" version of the exam. The IDE Program recently discussed ideas for how we could further help our students prepare for the FE exam, and each instructor was asked to evaluate the overlap of their course content with the applicable sections of the FE exam to identify opportunities for further alignment. Because Data Analysis is the only statistics course that most IDE students take prior to graduation, the statistical concepts assessed on the FE exam must be taught in Data Analysis.

The final influence on the course's learning objectives that we considered is the course equivalency (with regards to meeting prerequisite and graduation requirements) of the IDE and mechanical engineering versions of Data Analysis. The two courses have quite different course assignments and activities, but their course topics and learning objectives largely match [13]. The overlap in learning objectives likely stem from the original course proposal and curriculum being based on the mechanical engineering version of this class. As the engineering college at CU Boulder looks to streamline pathways to completion for students who change their major, it is important to try to preserve this course equivalency; thus, the topics and learning objectives of our redesigned Data Analysis course must continue to correlate closely with those of equivalent courses in the college, namely the Data Analysis course in mechanical engineering.

Review of Prior Work

Redesigning or modifying a measurement or engineering course for engineering students is a common endeavor. For example, Aung [14] revamped a mechanical engineering measurements lab based on student feedback and accounted for the lab being one of two courses in the degree that targeted the ABET student outcome related to conducting experiments and analyzing and interpreting data. Their new experiments included aspects of linear regression and validating theoretical models with experimental data.

Linear regression was repeatedly identified as a topic of emphasis when redesigning a measurement or statistics course. Chitikeshi et al. [15] integrated descriptive statistics and linear regression into an industrial instrumentation class for an engineering technology program. They chose to focus on the use of software for this analysis and deemphasized manual mathematical calculations. Burns and Hammond [16] described the multi-year redesign of a multidisciplinary statistics course, and they too decided to further prioritize linear regression—including multiple linear regression—and the use of software over hand calculation. Through a comprehensive analysis of course goals and constraints that included the review of ABET criteria, stakeholder requirements, and student feedback, they also concluded that their 10-week statistics course for engineers should put greater emphasis on experimental design, ANOVA, regression, the use of real-world data, and graphical visualization via software. Similarly, we collected feedback from many sources—including faculty, students, and employers—when determining the curricular priorities for Data Analysis.

When evaluating different types of assessments for a mechanical engineering course, Myszka [17] concluded that laboratory reports, quizzes, and design projects did not adequately address the students' working knowledge of the concepts covered in the course. While practicum exams take more time to administer and prepare, and are more difficult for instructors to grade, they improve the student's overall participation in the course, and more adequately address the learning outcomes for the courses. However, because of time constraints and the volume of course content, we ultimately decided not to include a practicum exam in the redesign of Data Analysis.

With regard to lectures and classroom activities, many statistic-course instructors have found benefits in a flipped classroom model, where students watch short lecture videos outside of class and engage in project or active-learning exercises in the classroom. Vidic and Clark [18] concluded that a fully-flipped statistics course for engineers enabled more personalized learning and instruction than a partially-flipped classroom. A study led by Motamedi [19] indicated that a flipped and "modified instructor-guided" pedagogy for a data analysis course for engineers yielded higher computational understanding and theoretical and statistical self-efficacy than a problem-based learning approach. However, problem-based learning tended to result in higher self-efficacy for using data analysis software. Similarly, Huang et al. [20] found that students in a project-based learning intervention were more likely than those in an online course to talk about the connection between statistics and their disciplines but not themselves. They posited that this phenomenon reflected that students involved in project-based learning activities were more inclined to regard themselves as a part of the engineering community.

The students in Motamedi's study [19] tended to prefer the flipped classroom because of its flexibility with their schedules, their ability to watch lectures when they felt motivated to learn and when they knew that they would be able to stay focused, and their increased engagement with short video content. A significant disadvantage was their inability to ask questions while learning the material; thus, students would go to class feeling confused and ill-prepared. Vidic et al.'s [18] study of flipped classrooms addressed this issue by allowing students to post their questions about the video lecture ahead of class, and the instructor addressed the questions at the beginning of each in-person class. IDE's Data Analysis course was partially flipped prior to this work, and these prior studies suggest we should consider fully flipping it as part of this redesign.

Methods

To determine the learning objectives of the course, we first consulted students, faculty, and staff. We gathered student feedback from past semesters of mid-term and end-of-semester surveys responses about the pace, content, and structure of the class. In general, students suggested maintaining the content coverage, pace, and project-based emphasis of the course. To gather the employer perspective, we spoke with a college-level administrator about the technical and professional skills that employers desired, based on a recent survey of companies who hire our graduates. The results of this survey suggested that employers are less concerned about students having specific technical skills and more concerned about their profession skills—written and oral communication, teamwork, critical thinking, etc. (B. Weihrauch, personal communication, March 11, 2022). Finally, during a faculty meeting, we asked the faculty of the IDE for their opinions of what the learning objectives of the course should be for both the measurement and statistics domains. We focused this discussion on enduring outcomes, using "what should the students know or be able to do five years from completing this course" as our guiding prompt. We then compared a synthesized list of possible enduring outcomes from the faculty with employer's desired skills of our graduates, the student outcomes from ABET, the statistical topics on the FE exam, and the learning objectives of the mechanical engineering version of the course. Through an iterative process and much discussion, we organized our learning objectives into three categories of decreasing priority: enduring understanding, important to know and do, and worth being familiar with.

After determining our curricular priorities, we decided on the evidence needed to evaluate the students' knowledge and skills in those areas. We emphasized the repeated assessment of enduring outcomes throughout the semester, and we also ensured that all good-to-know learning objectives were assessed at least once. It varied whether or not the worth being familiar with topics were assessed. Both formative and summative forms of projects, presentations, reports or portions of reports, quizzes, and homeworks were employed.

Lastly, we created the classroom activities and lectures. In general, we further adopted a flipped classroom pedagogy by recording more videos of short lectures that students watch outside of class. In accordance with prior research [18, 19], we preferred to have students watch lectures outside of class so that they had more in-class time to engage with hands-on and collaborative activities.

Results

Learning Objectives and Curricular Priorities

A synthesized list of learning objectives for Data Analysis, their curricular priority, and their associated assessments is presented in Table 1. The priority of each learning outcome is evident in how many assessments align with it. For example, we categorized students' ability to critique data visualizations and descriptive statistics for clarity and appropriateness as an enduring understanding, and there are over 13 assessments to collect evidence of students' progress toward that objective. Conversely, we classified two-way ANOVAs as worth being familiar with, and intend to make students aware of the method, without assessing them on the content.

Our decision to not include assessments or classroom activities related to two-way ANOVAs but including non-parametric methods may be the biggest difference in learning objectives between the IDE and mechanical engineering versions of the course. We feel non-parametric methods must be included in the course if students are expected to appropriately analyze the data that they collect as part of their culminating Design Your Own Experiment (DYOE) project. History has shown that students' DYOE data are often non-normal with small sample sizes.

Assessments

Table 2 provides a comprehensive list of the assessments that were created to evaluate the extent to which students achieved the learning outcomes of the course. Collectively, these assessments account for 92% of a students' grade in the class, with embedded questions in the online lecture videos (5%) and professionalism and participation (3%) making up the remainder. One notable exclusion from Table 2 is a poster presentation. The creation and presentation of a poster has been a long tradition of Data Analysis in both the IDE and mechanical engineering versions. However, because the vast majority of students in the course are IDE students who have created posters for three previous project-based courses, we decided to convert the presentation associated with the DYOE project from a poster to a slide presentation, which are more common in industry.

The DYOE is a project that students work on for about three-quarters of the semester, with intermediate progress checks. It requires students to design their own experiment, give a presentation on their experimental design, develop their own measurement system, collect and analyze their own data, and present their findings in a written report and a final presentation. The guidelines specify that they must incorporate an ANOVA.

The design and assembly of a kalimba (a traditional African thumb piano) and the design and build of a smart home security system constitute the other significant projects in the course. The kalimba project emphasizes the value of utilizing analytical (theoretical) models and empirical results in combination. Students must use measured values, including those from a tensile test that is used to find the modulus of elasticity of the material used for the kalimba tines, to predict the length of individual tines that will produce certain musical tones. They then validate their predictions with experimental results collected from a microphone and USB data acquisition system and discuss any discrepancies.

Table 1. We organized the learning objectives into three categories: enduring understanding (EU, highlighted), important to know and do (IKD), and worth being familiar with (WF).

Topic	Learning Objective	Priority	Assessment
Data Visualization and Numeric Descriptive Statistics	Critique data visualizations and descriptive statistics for clarity and appropriateness	EU	HW1, 3, 5-7, 9, 11-13; P1-3; Q
	Create visualizations and calculated descriptive statistics for continuous and ordinal data	IKD	HW1, 3, 5-7, 11-12; P1-3; Q
	Calculate a weighted average	IKD	Q
	Identify and create visualizations and descriptive statistics for categorical/nominal data	WF	HW1
Data Analysis Methods	Differentiate between different data types and recall that different types of data are analyzed differently	EU	HW1, 10-12, P3; Q
	Employ parametric methods for continuous data	IKD	HW1, 3-9, 11-12; P1, 3; Q
	Utilize non-parametric methods for ordinal or non-normal data	IKD	HW1, 11-12; Q
	Understand and apply methods for analyzing categorical/nominal data, including binomial data	WF	HW1, 10
	Recognize situations when a two-way ANOVA is needed	WF	
Uncertainty	Explain the concept of a confidence interval and why every measurement has uncertainty	EU	HW4, 6-9; P1, 3; Q
	Paraphrase the concept of propagation of uncertainty	EU	HW8; Q
	Calculate a best guess and confidence interval for an unknown true value of a measurement	IKD	HW6-8, P3
	Use the propagation of uncertainty equation	IKD	HW8
Distributions	Identify different distribution shapes, including normal, skewed, uniform, and bimodal	EU	HW 1, 3-9, 11, P3, Q
	Explain and utilize the Central Limit Theorem	IKD	HW4, HW11, P3
	Recognize natural limits in a dataset	WF	
Statistical Ethics	Critique the ethics of a particular statistical analysis that may or may not support the analyst's conclusions (e.g., eliminating outliers, changing parameters)	EU	HW9; Q
Regression and Correlation	Employ linear and non-linear regression	EU	P1-3; Q
	Explain the difference between correlation and regression	IKD	HW12; Q
	Interpret and use multiple regression	IKD	HW12
Data Acquisition Systems and Signals	Identify elements of a data acquisition system and discuss rate (sampling frequency), resolution, and range	EU	HW2-3, 8, 11; P1-3; Q
	Summarize the characteristics of a "digital" (analog, binary) or analog signal	EU	HW2; P2-3; Q
	Perform a sensor calibration and explain how that reduces the uncertainty in the measurement	IKD	HW8, 11; P2, 3
	Recognize the difference between "digital" signals and digital communication (e.g., serial)	WF	
Experimental Design	Thoroughly plan an experiment before conducting it, considering why, who, and how, including the variables of concern, measurement equipment, and analysis methods	EU	HW3, 11; P1-3
	Design and conduct an experiment that compares measured data to a theoretical or analytical model	IKD	P1, 3

Note: HW = homework, P = project, Q = quiz (see Table 2 for more information).

The smart home security system requires students to incorporate sensors, actuators, and indicators of different types, with a custom LabVIEW program controlling all hardware. As part of the project, students must calibrate an analog sensor of their choice and incorporate it into their design.

To have students practice their writing abilities prior to delivering a large report, we incorporated writing assignments into many of the homework assignments. For example, for HW1 students have to write the Results and Discussion sections of a report. For HW3, they must write a Methods and Results section.

Table 2. A variety of homework (HW), project, and quiz assessments provided evidence of students' progress toward the learning objectives.

Assessment	Description
HW1	Descriptive statistics and visualizations
HW2	Introduction to LabVIEW (a coding environment tailored to data acquisition)
HW3	Collect data and find descriptive statistics for an experiment comparing light intensity between two classrooms
HW4	Central Limit Theorem
HW5	Descriptive statistics in Matlab (another tool)
HW6	Inferential statistics: 2-group comparison (t-tests)
HW7	Inf. stats: 3+ group comparison (ANOVA)
HW8	Propagation of uncertainty
HW9	Statistical ethics
HW10	Binomial distributions
HW11a	Non-parametric group comparisons (2-group)
HW11b	Non-parametric group comparisons (3+ groups)
HW12	Multiple regression
HW13	Critique of published statistical graphic or table
Project 1	Theoretical models and experimental results--how do they complement and differ? (Kalimba project) Video summary and full report
Project 2	Smart Home control system video and (partial) report (DAQ inputs and outputs; calibration)
Project 3a	Design Your Own Experiment (DYOE): Experimental design presentation
Project 3b	DYOE: Presentation and Report
Quizzes	Weekly quizzes (with a partner) that are cumulative and focus on assessing students' conceptual understanding of course topics

Activities

Classroom activities and pedagogy are largely influenced by instructor preference and what resources are available. Therefore, we will only highlight the general structure of the course and a few of our classroom activities.

In general, we flipped our classroom. We recorded videos that students watched every week outside of class. These are a combination of screencast videos recorded by the instructor and publicly-available, online videos. All videos utilize the PlayPosit platform, which enabled us to embedded questions that tested students understanding of the main concepts. In class, we briefly summarize the main points of the videos and answer any questions. Then, we move on to demos, hands-on activities, or group-based assignments.

A few of our most popular demonstrations relate to aliasing. One demonstration utilizes a cantilevered beam (about 30” long) mounted on a vibration shaker. We excite the beam at its natural frequencies and use a stroboscope to simulate a sampling frequency. If the stroboscope frequency is at least twice the vibration frequency of the beam, we accurately capture the motion of the beam. However, we demonstrate that a stroboscope frequency of exactly twice the vibration frequency can lead to the appearance of a static beam (with or without a given deflection). We then also demonstrate the phenomenon of aliasing, where the beam appears to be oscillating a much lower frequency than reality. We include a discussion of mode shapes and nodes, and the students love running their finger along the beam and feeling the node of the mode shape. We do a similar demo with a box fan that has a bright piece of tape on one of the fan blades.

A second demonstration related to measurement range and resolution involves a song clip that we resample with a specified range and number of bits. Students (and instructors!) are always amazed that you can make out the lyrics and music with a resolution as low as a single bit.

For the statistics portions of the course, we try to incorporate as many active-learning activities as possible to minimize the time lecturing. For example, we have students analyze real data from Netflix when learning about data types, descriptive statistics, and data visualizations. When introducing t-tests, we have all students at a white board, drawing out each step of the analysis process. We also do a fun activity (with treats!) comparing the amount of cream in a regular Oreo to that of a Double Stuf Oreo—is there truly twice the cream? We also try to use real-world and relevant data sets as much as possible. For example, we have a discussion about the gender pay gap and then do an analysis using real data. We discuss micro-aggressions and then use data from a CU Boulder survey in a binomial distribution assignment, and we investigate COVID death rates across racial/ethnic groups.

As mentioned previously, one intended outcome of this work was to interweave the concepts and activities of measurement and statistics more than we have in the past. This gives students opportunities for deliberate, distributed practice to improve their learning [1]. One example of how we connected and sequenced measurement and statistic concepts is that we have students design and execute an experiment involving the measurement of light levels in two different classrooms. We later utilized the data the students collected in a descriptive statistics and two-group comparison activity. Similarly, students will collect experimental data to use in a non-parametric, group-comparison analysis. The last example we will highlight is the natural pairing of sensor calibration with linear regression concepts.

Discussion

The implementation of this course redesign is being classroom tested in Spring 2023. One concern of this curriculum design is the pace at which topics must be introduced. If our just-in-time pedagogical decisions require more time than anticipated for certain topics or assignments, we plan to reduce the priority of multiple linear regression to a good to be familiar with, in which students will be exposed to the concept but will not be assessed on it.

A limitation of our course redesign is its narrow focus—a specific course at a specific university. For instructors who teach similar courses in measurement and statistics or for curriculum committees considering course consolidations, we expect our work to be applicable and useful. Additionally, we posit that our results are also applicable to engineering programs with independent courses in measurement and statistics because many of the learning objectives are program-level objectives that align with ABET criterion and the FE exam.

While we did include ABET criteria and the FE exam topics in our analysis, we did not directly solicit corporate feedback. Part of our justification for this is that in our college survey of employers, the most desired knowledge and skills from employers were related to professional skills, not specific technical skills (B. Weihrauch, personal communication, March 11, 2022). With our emphasis on teamwork, written and oral communication, critical thinking and problem solving, and ethics, we are developing and assessing students' professional skills throughout the course. Additionally, the ABET organization and accreditation criteria are governed by members of over 35 professional and technical societies, thus intrinsically linking the ABET requirements to the educational outcomes desired by industry.

Our planned future work for this project includes a reevaluation of our curricular priorities, assessments, and activities after the curriculum has been classroom tested in Spring 2023. As customary for all IDE courses, at the end of the semester we will have another professor in IDE lead an evaluation session that includes the compilation of strengths of the course and areas for improvement. The students then individually vote on the extent to which they agree or disagree with each strength or area of improvement. Additionally, the students will be given an end-of-the-semester survey that will ask course-specific questions about the pace, curriculum, and pedagogy of the course. All course feedback, including results from the institutionalized Faculty Course Questionnaire (which asks students to self-report the extent to which the course helped them achieve each of the seven ABET student outcomes), will be discussed during an IDE faculty meeting to evaluate the course redesign and identify future adjustments. Thus, the feedback from students, course instructors, and other IDE faculty will guide future course improvements.

Conclusion

This paper describes our backward-design approach to the redesign of a measurement and statistics course. The most challenging aspect of the project was determining the curricular priorities because the course content spans the expansive fields of measurement and statistics, the course must help students develop the ABET student outcomes and prepare them for the FE exam, the measurement and statistics content must be interwoven so as to provide opportunities for deliberate, distributed practice of concepts and skills throughout the semester, and its learning objectives must maintain sufficient alignment with other similar college courses to maintain course equivalencies. While we describe the redesign of a specific course, the research-based approach employed would be applicable when redesigning other engineering courses with learning objectives that face similar multi-faceted constraints and expectations.

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