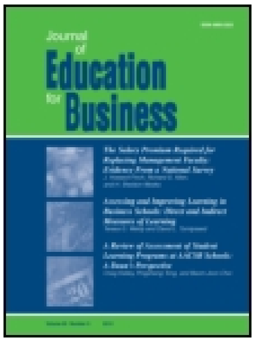

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Linear Programming Across the Curriculum

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Linear programming (LP) is taught in different departments across college campuses with engineering and management curricula. Modeling an LP problem is taught in every linear programming class. As faculty teaching in Engineering and Management departments, the depth to which teachers should expect students to master this particular type of modeling is often discussed. Does a student's understanding of this critical concept differ across the curriculum? The authors look at students' abilities to model LP problems in two different departments: Industrial Engineering and Management. The authors compare the results and look for differences and reasons for those differences.

Keywords: curriculum, linear programming, modeling

Modeling a linear programming problem is an essential part of a course in linear programming. However, a class in linear programming can be taught in many different departments. At one particular large state research university, this topic is introduced to sophomores in industrial engineering and juniors in various management and computing curricula. As faculty teaching these courses, with backgrounds in industrial engineering, we often compare their experiences teaching these topics. Does a linear programming model look the same in a business class as it does in an engineering class? Can the same concept be taught differently and still have the students understand it in the same manner? We are interested in determining if the intent of what appears to be the same learning objective could differ depending on the learning environment. We both believe our courses should prepare students to model problems as linear programs. How does the department of offering impact how we perceive achievement of this learning objective?

We both have a theoretical educational background (Industrial Engineering and Mathematics); however, the departments in which we teach are more applied than those in which we were trained. We have a common expectation of what should be learned by the students and hope that the students are interested and invested in the material being taught. However, we acknowledge that there are differences in the programs in which we teach that impact the direction of the courses and learning objectives, despite the inherent similarity of the larger concept.

STATEMENT OF PROBLEM

We are interested in viewing the comprehension of some basic concepts common to a particular type of mathematical modeling when they are taught in different academic departments. This particular mathematical modeling is called mathematical programming in general, and we focus on a subset called linear programming.

A linear programming model consists of three parts: a set of decision variables, an objective function, and a set of constraints. This is true of any linear programming model. The set of decision variables are definitions of the decisions that are to be made. The objective function is a mathematical function that is a measure of the performance of interest, most commonly to maximize profit or minimize cost. The set of constraints are mathematical equations or inequalities that restrict the values of the decision variables, which can be any real values that satisfy these constraints. In linear programming, the constraints and objective must be linear functions of the decision variables.

This experiment was conducted in two linear programming classes from a public research university with an enrollment of 16,432 undergraduates in the fall of 2012. Approximately 54% of these students were men; 84% were Caucasian; 69% were in-state residents (Clemson Institutional Research, 2013). The two academic departments included in the study were management and industrial

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engineering. The sample consisted of one linear programming class in an industrial engineering department and a decision modeling class in a management department.

A description for each course as listed in the university catalog is given in Table 1, along with other relevant course information.

Some additional nuances differentiated these courses. The management course was not a prerequisite for any other required courses in the relevant majors and is sometimes taken in the last semester of the student's academic career. In contrast, the industrial engineering course was on the critical path through the curriculum and had been taken no later than the first semester of the junior year. The industrial engineering course was most often taken in the first semester of the sophomore year, being a prerequisite for at least four later courses.

Some structural similarities existed in the courses. Each class used the same percentage of the semester for teaching linear programming (about 65%). The instructors had similar teaching styles in that they taught modeling by hand (algebraically) and using software. Both sets of students are evaluated on modeling by hand and the implementation using software.

We hypothesized the students in the two departments would differ in their understanding of linear programming. We believed the difference in the mathematical abilities between industrial engineering students and management students would create differences in their understanding of linear programming concepts. We also hypothesized that the placement of a course in the curriculum would impact how much students care about a course, affecting how much effort they would give to understanding the material.

LITERATURE REVIEW

Several studies might help us predict potential differences between disciplines. LeFevre, Kulak, and Heymans (1992) examined what makes college students choose among degrees of differing mathematical content. They find that students having higher levels of mathematical anxiety avoided degrees with moderate or high mathematical content. Those students taking the class in the management department have lower mathematical content in their degrees than the students in the industrial engineering department. According to LeFevre et al., business would be classified as a major having a moderate mathematical content (having at least two mathematics entrance requirements and requiring between three and six mathematics courses for the major). Engineering would be classified as having a high mathematical content (having at least two mathematics entrance requirements and requiring more than six mathematics courses in the major). They also find that students with higher arithmetical ability choose degrees with higher mathematical content. LeFevre et al. concluded that students with better attitudes toward mathematics tend to choose degrees with higher mathematical content, as do those who are more fluent in arithmetic. Through numerous studies Hackett (1985) along with Betz (Betz, 1983; Hackett & Betz, 1989) found that math self-efficacy directly affects major choice. Those with lower math self-efficacy expectations would gravitate toward nonmathematical majors.

Pritchard, Potter, and Saccucci (2004) noted that students having weaker quantitative skills ended up in management and marketing as a major as compared to other business majors such as accounting and finance that are

TABLE 1
Summary of Course Characteristics

Course	Management	Industrial Engineering
Level	Junior	Sophomore
Required for	Management major Computer Information Systems major Business Information Systems minor	Industrial Engineering major
Offering pattern	Every semester	Fall only
Typical section size	40	80–90
Catalog description	Exploration of ways in which management science decision models can help in making sound managerial decisions. Problem solving is Excel based. Topics include linear programming, project scheduling, and simulation.	Introduction to operations research models, including linear programming, integer linear programming, transportation and assignment problems, and network flows.
Prerequisites by topic	First semester business calculus, first semester statistics; comfort with computer applications (MS Office suite)	First semester engineering calculus
Relevant learning outcomes	Students will be able to • Formulate several different kinds of linear programming models. • Classify several different types of linear programming models.	Students will be able to • Model basic deterministic mathematical programs • Resolve basic mathematical programs using common optimization algorithms.
Textbook	*Introduction to Management Science: A Modeling and Case Studies Approach With Spreadsheets*, 4th edition (Hillier & Hillier, 2011)	*Operations Research*, 4th edition (Winston, 2004)
Software for solving linear programs	Excel and Solver	AMPL (command line driven)

more computationally intensive. Zanakis and Valenzi (1997) looked at student anxiety and attitudes in business statistics. They found student grade in the course was primarily influenced by initial math anxiety and computer experience.

Anderson et al. (2000) gave a revised version of Bloom's taxonomy that told us about the types of competence we expect the students to demonstrate. There are six levels of learning: remembering, understanding, applying, analyzing, evaluating, and creating. We used this framework to guide our study.

METHOD

In the semester of the study, neither instructor changed any element of the course. The only intervention in the courses involved the administration of the study questions in one class section. We created two linear programming problems for the students to analyze. The first is a description of a blending problem for which the students should formulate a linear programming model. The second requires inspecting, evaluating and potentially correcting a provided formulation (which happens to be incorrect but the students are not provided this fact). The first question is intended to assess the creating level of Bloom's revised taxonomy while the second is targeting skills in the evaluation level. Toward the end of the semester each professor administered the questions to her class. The class was encouraged to take part in the survey, but there was not any external motivation given, such as extra credit.

A rubric for the first question (see Appendix A) was established that concerned the definition of the decision variables, the objective function, the blending constraints, the 1 ton constraint, and the sign restrictions. The rubric for the second question (see Appendix B) was based on the decision variables, the objective function, the supply constraints, the transshipment constraints, the demand constraints, the capacity constraints, and the sign restrictions. The responses were graded by the professor teaching the class and graded again by the other professor. Based on the literature, we investigated differences between performance on question type, in aggregate and by course. We also evaluated whether the instructors implicitly have different standards for competence by examining differences between grading results.

RESULTS

Students were not required to participate in the exercises, nor were they given extra credit, in keeping with the institutional review board–approved study protocol. Thirty-eight of the 64 students in the management course participated, while the industrial engineering course's survey was completed by 76 of the 87 enrolled students. Some of these missing observations were due to absences, but some were due to choosing not to participate.

Preprocessing

Because the scores for the questions were not normally distributed (based on a histogram), the Wilcoxon signed rank sum test was used to determine if there were differences in the grading between the two people who graded each question. There were no significant differences between the two graders for any question (p values ranged from .53 to 1), so it was confirmed that the instructors interpreted the rubrics consistently. Because no differences in means were found, the grade from the actual instructor of the class was used for further analysis.

We discarded the responses for unanswered questions. The management class had 16 scores removed for question 1 and six for question 2. The industrial engineering class had six scores removed for question 1 and three for question 2.

All Student Results, Aggregated

We used the Wilcoxon rank sum test to determine if there was a difference in means (of percentage correct) between the two questions, when aggregating all student responses together. We found there is not a difference in means between the two types of questions—formulate or correct the formulation ($p = .24$). Students, in aggregate, do not appear more capable of making corrections on a formulation than creating the entire formulation, despite creating being a higher order skill than evaluating, in Bloom's revised taxonomy.

Comparing the Questions in the Same Courses

When considering the differences between questions for students in the same classes, the management students show a statistically significant difference in the percentage correct for the two questions ($p = .0002$). The question that creates a formulation averages 0.233 for the percentage correct; the correct the formulation question has an average of 0.459 for the percentage correct. These results are supported by Bloom's revised taxonomy; creating is a higher order skill than evaluating. management students have lower mathematical skills than industrial engineering students, hence, lower scores on the higher order skill.

The industrial engineering students also show a statistically significant difference in the percentage correct for the two questions ($p < .0001$). However, they scored better on the question asking to create a formulation (average $=$ .630) than they do on the correction question (average $=$ 0.501). This supports the idea that those with higher and more confidence in mathematical skills would comprehend more on a higher level of learning.

Comparing the Questions Between Courses

There were no statistically significant differences between the groups for the formulation correction question ($p = .25$). The management and industrial engineering averages were 9.18 points and 10.01 points of 20, respectively. Both groups appear to be equally competent at evaluating. There ere statistically significant differences in the scores among the disciplines for the formulation question ($p < .001$), at the creating level. Management students scored an average of 4.19 points and the industrial engineering students averaged 11.34 points of 18, respectively.

DISCUSSION

In the discussion, we consider two aspects of the experiment conducted: the actual statistical results and the environment in which it was conducted.

Student Results

We summarize the results from Section 5 in Table 2.

The finding that there is not a statistically significant difference between the aggregated scores of the two sets of students can be explained by the opposite findings within courses. The higher scores of the industrial engineering students in Creating were offset by the management student scores in evaluating. We utilize the revised Bloom's taxonomy to understand why industrial engineering and management students have different strengths. This result provides instructors a reason to ask one type of question to one set of students and not the other. We posited that students in industrial engineering were more responsible for model creation in general and students in management and related disciplines would be called on to evaluate models created by others. The differences in mathematical skills need not be the only reason for designing the courses differently—the intent of the curricula actually differs and so the courses should be different as well.

Experimental Environment

Overall, we make the following observations about our study that do not revolve around the direct issues but about the nature of the courses used. First, the participating student response rate in the industrial engineering department was 95% for question one and 96% for question 2 (overall, 82% of enrolled students responded to question 1 and 84% to question 2). The management department had a participating response rate of 58% for question one and 84% for question two (overall, 34% of enrolled students responded to question 1 and 50% to question 2). Those in the management department are taking a class that is required of their major but not necessarily one that they might enjoy or have confidence in, based on the instructor's experience with the course. The students in the management department are taking a class that relies heavily on mathematics and the majority of them would admit they are not confident in their math skills. They are less engaged with the material, based on the instructor's experience. Most students in the industrial engineering department have more advanced math skills, as evidenced by their progression in their major. The modeling class in the management department is known to have a high rate of Ds and Fs (typically around 18%), in contrast with a 5% rate of Ds and Fs in the industrial engineering course. LeFevre et al. (1992) provided an understanding of the unresponsiveness of the management students, because those students who do not have a good attitude toward mathematics likely do not have any intrinsic motivation to complete the exercise.

The IE class is taken by students in either their third or fifth semester; those are the only two options, as it is a direct prerequisite for three other required courses for that major. They could have had anywhere from one to three math classes prior to taking IE 280. Students in industrial engineering, even if they do not internally find motivation for mastering the material, feel pressure to comprehend the material to perform well in later classes. The MGT 312 class can be taken as early as the third semester or as late as the last semester. It is a prerequisite for just one other class that is not required for the major. However, typically students are in at least their fifth semester when taking the class. The students in this class, unless they plan to take the

TABLE 2
Results

	Creating	Evaluating
All students	No statistically significant differences	
Within course	Statistically significant difference: industrial engineers are better at creating than evaluating	
	Statistically significant difference: management students are better at evaluating than creating	
Within question	Statistically significant difference: industrial engineers are better at creating than management	No statistically significant differences between student types

elective that requires linear programming, know that their ability to formulate linear programs will not directly influence their performance in any other course. Perhaps the lack of accountability for the material further demotivates the students to such a degree that almost every semester, a poor grade in this course delays graduation for a few students. Its very reputation may induce anxiety in the students, leading to a lack of engagement. We hypothesize that student engagement in material does not only depend on the course itself but on where the course is placed in the curriculum, both in terms of prior mathematical exposure and later accountability for the material.

CONCLUSIONS

In this study, students were asked to engage with mathematical programming modeling, a topic that is found in management and industrial engineering curricula. We asked each set of students to complete the same tasks and blindly and independently evaluated the results, yielding scores for each student and each question. We examined the differences based on major. Given the results of the tests for differences in means, management students performed the least well in both formulating an linear programming model and correcting an linear programming formulation. This conclusion, along with the fact that management students had the lowest response rate for both questions, suggests that management students, who are less likely as a whole to be confident in their math skills, do not comprehend linear programming modeling in the same way as do students in an industrial engineering department. The placement of these courses in their respective curricula may further undermine or strengthen student perception of their importance, and is out of the control of the instructors. This provides instructors of mathematical modeling, such as linear programming, in those majors that tend to be selected by students with worse attitudes toward mathematics with a quandary: how to convey the importance and relevance of these topics to students who feel to the contrary. This may be even more challenging for those instructors who had good attitudes toward mathematics and selected majors that had high mathematical content. These fields are dominated by such instructors. What exactly do students in fields such as management and industrial engineering need to know about linear programming, relative to their career needs, not the biases of their instructors? Developing such objectives, based on student need instead of instructor bias, will facilitate better experiences for all parties involved. We also can justify, based on these results, the offering of different classes for different majors, even though the topics are nominally the same. Colleges may feel that several courses covering the same topics taught in different departments are unnecessary; however, our findings indicate to the contrary if the goal is to educate students in the most relevant way. We encourage professional organizations such as INFORMS and its Forum on Education to facilitate this discussion for the improved education and experience of one of its largest sets of students.

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APPENDIX A

Formulate the Following Linear Programming Model

Your company wants to blend a new alloy of 30% tin, 40% zinc, and 30% lead from several available alloys having the following properties:

Alloy Property	1	2	3	4	5
Percentage of tin	60	30	35	25	50
Percentage of zinc	25	40	55	50	35
Percentage of lead	15	30	10	25	15
Cost ($/lb)	24	28	30	25	26

Your company wants to make 1 ton beams of this new alloy. How should these alloys be blended in order to do this at the minimum cost per beam?

APPENDIX B

Correct the Formulation of the Following Linear Programming Model

Coffee tables are manufactured at three plants - A, B, and C. Plant A can produce 250 tables weekly, plant B can produce 300, and plant C can produce 200. Once made, these tables are shipped to two warehouses (G and H); from there, they are shipped to four companies – J, K, L, and M. From plant A, it costs \$38 to ship a table to warehouse G and \$47 to warehouse H. From plant B, the shipping cost per table to warehouses G and H is \$32 and \$37, respectively. To ship a table from plant C, it costs \$46 to warehouse G. The shipping costs from warehouse G to companies J, K, L, and M are \$28, \$25, \$32, and \$34, respectively. Warehouse H can ship a table for \$40 to company J, \$38 to company K, \$29 to company L, and \$33 to company M. There is a limited truck capacity, so only 200 tables per week can be shipped from plant B to warehouse G and only 150 can be shipped from plant C to warehouse G. The demand at company J is 150 tables per week; company K's demand is 200, while L and M demand 225 and 175 tables per week. How should be tables be shipped in order to minimize the shipping cost?

X_{ij} = # of tables to ship from i to j where i = j = A, B, C, G, H, J, K, L, M

Min $38X_{AG} + 47X_{AH} + 28X_{BG} + 37X_{BH} + 46X_{CG} + 28X_{GJ} + 25X_{GK} + 32X_{GL} + 31X_{GM} + 40X_{HJ} + 39X_{HK} + 29X_{HL} + 33X_{HM}$

ST:

$X_{AG} + X_{AH} = 250$	$X_{GJ} + X_{GK} + X_{GL} + X_{GM} = -150$	$X_{CG} <= 150$
$X_{BG} + X_{BH} = 300$	$X_{HJ} + X_{HK} + X_{HL} + X_{HM} = -250$	all $X_{ij} >= 0$
$X_{CG} + X_{CH} = 200$	$X_{BG} <= 200$	