



INFORMS Transactions on Education

Publication details, including instructions for authors and subscription information:
<http://pubsonline.informs.org>

Motivation and Analytics: Comparing Business and Engineering Students

Natalie M. Scala, Stella Tomasi, Andrea Goncher, Karen M. Bursic

To cite this article:

Natalie M. Scala, Stella Tomasi, Andrea Goncher, Karen M. Bursic (2018) Motivation and Analytics: Comparing Business and Engineering Students. INFORMS Transactions on Education (): <https://doi.org/10.1287/ited.2017.0187>

Full terms and conditions of use: <https://pubsonline.informs.org/page/terms-and-conditions>

This article may be used only for the purposes of research, teaching, and/or private study. Commercial use or systematic downloading (by robots or other automatic processes) is prohibited without explicit Publisher approval, unless otherwise noted. For more information, contact permissions@informs.org.

The Publisher does not warrant or guarantee the article's accuracy, completeness, merchantability, fitness for a particular purpose, or non-infringement. Descriptions of, or references to, products or publications, or inclusion of an advertisement in this article, neither constitutes nor implies a guarantee, endorsement, or support of claims made of that product, publication, or service.

Copyright © 2017, The Author(s)

Please scroll down for article—it is on subsequent pages




INFORMS is the largest professional society in the world for professionals in the fields of operations research, management science, and analytics.

For more information on INFORMS, its publications, membership, or meetings visit <http://www.informs.org>

Motivation and Analytics: Comparing Business and Engineering Students

Natalie M. Scala,^a Stella Tomasi,^a Andrea Goncher,^b Karen M. Bursic^c

^aTowson University, Towson, Maryland 21252; ^bCharles Sturt University, Bathurst, NSW 2795; ^cUniversity of Pittsburgh, Pittsburgh, Pennsylvania 15260

Contact: nscala@towson.edu,  <http://orcid.org/0000-0003-2851-134X> (NMS); stomasi@towson.edu (ST); andrea.goncher@gmail.com,  <http://orcid.org/0000-0002-1913-408X> (AG); kbursic@pitt.edu,  <http://orcid.org/0000-0003-1438-9072> (KMB)

Received: January 8, 2016

Revised: June 13, 2016; April 21, 2017; July 15, 2017; July 30, 2017


Accepted: August 8, 2017

Published Online in Articles in Advance: November 9, 2017

<https://doi.org/10.1287/ited.2017.0187>

Copyright: © 2017 The Author(s)

Abstract. Data analytics is a foundational topic for engineering as well as business students given its importance in subsequent coursework and curriculum. Many common, interdisciplinary analytical topics exist between the engineering and business fields; undergraduate students may approach learning those topics in various ways depending on program or major. This research examines differences in performance on analytics between engineering and business students that may be explained by differences in motivation and attitude. We use a survey and a lecture on trendlines with a common homework assignment to compare the two groups of students. Instructors of an engineering and a business course that incorporate analytics gave the same lecture on the use of spreadsheets to analyze trendline data, assigned the same individual homework assignment, and administered an end-of-module survey. The survey was built from the established MUSIC[®] Model of Academic Motivation. Analysis of the student data will address differences in motivation and how the program or major impacts student perception of analytical problem solving and contributes to performance on related assignments. We discuss quantitative and qualitative differences between engineering and business majors, concluding with a discussion of future work and some strategies for educators to use when teaching analytics.

 **Open Access Statement:** This work is licensed under a Creative Commons Attribution NonCommercial-NoDerivatives 4.0 International License. You are free to download this work and share with others, but cannot change in any way or use commercially without permission, and you must attribute this work as "INFORMS Transaction on Education. Copyright © 2017 The Author(s). <https://doi.org/10.1287/ited.2017.0187>, used under a Creative Commons Attribution License: <https://creativecommons.org/licenses/by-nc-nd/4.0/>."

Funding: The Towson University College of Business Summer Research Grant Program supported this research.

Keywords: developing analytical skills • interdisciplinary teaching • spreadsheet modeling • teaching engineering • teaching with technology

1. Introduction and Motivation

Developing quantitative and statistical skills is essential for engineering students as well as business students. The majority of business students consider quantitative courses as the most difficult courses in the business curriculum (Brookshire and Palocsay 2005). In recent years, data analytics has become a required course in many business curriculums. These courses may be newly designed or built from existing courses; Wilder and Ozgur (2015) define courses that can encompass a full business analytics program. Quantitative skills, and specifically data analytics, are also foundational course material for engineering programs. Many of these quantitative skills are taught in both programs, and the term *analytics* can be broadly applied to these interdisciplinary topics.

Our research aims to address two goals: (1) examine motivation of engineering and business students

towards data analytics, and (2) examine differences in attitude toward data analytics between the two major groups. Thus, this research will provide insight on teaching analytical concepts to business and engineering students. In this study we attempt to answer two questions:

1. Are there differences in motivation toward analytics topics between business and engineering students?
2. How does the field of study and attitude towards analytics influence a student's performance on data analytics assessments?

We provide insight into understanding differences between engineering and business students as well as improving student success and achievement. The research also suggests ways in which instructors can better connect with students and motivate them in both groups, especially when teaching interdisciplinary analytical topics.

Academic motivation has been regularly studied in the engineering education literature, but research is lacking in the business education literature. The motivation literature in engineering education has examined motivation in general and motivation of first year engineering students. Examples include Baillie and Fitzgerald (2000), who identified problem areas for engineering students at risk of demotivation, and Jones et al. (2010), who reported that several motivation constructs, including expectancy- and value-related beliefs, have different effects on engineering students' achievement and career plans.

Prior studies have shown that students who leave engineering mostly do so during their first year (Besterfield-Sacre et al. 1997). Students who leave engineering often switch to business programs (Ohland et al. 2008) or general studies (Santiago and Hensel 2012). A case study from a retail operations course taught in a business school and an industrial engineering program found that engineering students chose the course to apply concepts from operations management, while business students sought a framework for analyzing and discussing concepts (Van Woensel et al. 2010).

Specifically, this research assesses and compares student motivation among business and engineering students who are learning interdisciplinary analytics. We compare students in business and engineering programs and examine average test assessment scores, average motivation, and the tie between student performance and motivation in both groups.

2. Relevant Motivation Theories

2.1. Student Attrition

Engineering students leave the major for three main reasons: (1) the field does not match student interest; (2) academic difficulty; and (3) perceived inability to succeed in major (Santiago and Hensel 2012). While business is the most common destination for students leaving engineering, engineering students still have the highest rate of persistence among disciplines, and engineering students are similar to other students in terms of classroom engagement, faculty interaction, educational outcomes, and institutional engagement (Ohland et al. 2008). If students are similarly engaged across majors, then instructors of cross-listed courses can focus their efforts on determining specific motivational interventions for students from different majors to increase persistence in their course.

2.2. MUSIC® Model of Academic Motivation

The MUSIC® Model of Academic Motivation, proposed by Jones (2009), is based on a social-cognitive theoretical framework that includes five components that instructors should consider in design: eMpowerment, Usefulness, Success, Interest, and Caring. When instructors can identify and support one or more of these components, students are more motivated to engage

in their learning, which results in increased learning (Jones 2009).

Empowerment refers to the amount of perceived control that students have over their learning. This component is based on self-determination theory (Deci and Ryan 1985), where individuals who are empowered feel they have the ability to make their own choices and are responsible for the behavior they exhibit. The Usefulness component states that the content of the course should be useful to students' short- and long-term goals, as students' motivation is influenced by their perceptions of the usefulness of what they are learning for the future (Eren 2009). Research shows that students, regardless of major, who perceive their tasks to be less relevant to their goals are less motivated than those students who understand how the tasks are related to their future goals (Simons et al. 2004).

The third component, Success, is based on the fact that students need to believe they will succeed in the course if they have the knowledge, skills, and make sufficient effort (Jones 2009). Based on this component, the course should be challenging and provide enough clear expectations to which students can adhere to be successful. This component is similar to the self-efficacy theory where those who believe they can be successful will thus be motivated to do well (Bandura 1997). The fourth component, Interest, is based on the need to provide interesting topics and activities in the course to keep students motivated. Jones (2010) discusses two types of interest, i.e., situational and individual, which are based on Hidi and Renninger (2006). Situational is temporary and based on the environment, while individual is based on personal value and is more internally motivated. The last component, Caring, describes how students are more motivated in the course if they feel that their professor or instructor cares about their success (Jones 2010).

The MUSIC® Model of Academic Motivation has been used to assess student motivation in a variety of settings, including online instruction, engineering capstone courses, design studios, and middle school education; a full list of related studies is available in Jones (2015a). To our knowledge, the model has not been used with analytics or in a comparative study. We contribute such analysis and use the model to assess student motivation and drive when learning analytics. Such an assessment is beneficial, as students' attitudes, interests, and values are powerful predictors of subsequent behavior (Popham 2005). Insights gained from this study can be applied to design analytics courses specialized for engineering or business students to best suit student needs, interests, and values.

3. Methodology

3.1. Sample and Study Design

To address the research questions, we examine two groups of students, i.e., business majors at a large public

institution in the Mid-Atlantic region and engineering majors at a large semi-public institution in the Northeast United States. Both universities have total enrollment between 17,000 and 23,000 students each. A total of 94 business students enrolled across three sections of a core course on analytics and project management and 79 engineering students enrolled in one section of a core course on introductory engineering analysis were asked to participate.

One engineering professor taught the engineering students, while one business professor taught two sections of the business course and another business professor taught the third business section. Consent involved contributing the student's submission of a homework assignment to the study and participation in an online survey. The homework was an individual assignment that was part of the course at each university. Students had to submit the homework assignment and complete the survey by a certain deadline to be counted as participating.

Of the 79 engineering students, 63 completed the survey and the assessment, for a response rate of 79.7%. Of the 94 business students, 68 completed the survey and the assessment, for a response rate of 72.3%. The overall response rate for all students was 75.7%. Of the participating business students, 59% identified as male and 41% identified as female. Of the participating engineering students, 65% identified as male and 35% identified as female. For race and ethnicity, 12% of business students identified as African American, 16% as Asian, 72% as Caucasian, 1% as Hispanic, and 9% as Other. For engineering students, 8% identified as Asian, 87% as Caucasian, and 5% as Other. To mitigate differences between the student groups and universities, both groups were presented the exact same lecture notes on trendlines (a common analytics topic) using Microsoft Excel (a common analytics software package). Trendlines is an interdisciplinary concept and useful for students as a prerequisite to other courses during their collegiate study; the core business and engineering classes at each school teach trendlines as part of the analytics or quantitative skills curriculum. Excel is a common spreadsheet instructional tool in analytics courses. Popular introductory analytics textbooks incorporate Excel as the delivery method (e.g., Evans 2013, Camm et al. 2015). With Excel, students tend to be interested in lecture, as spreadsheets play a vital role in analytics and are essential to business (Grossman 2006). Excel is also commonly used in science and engineering courses (Singh and Siddiqui 2009). Slides and lecture notes for the lesson in our study were coordinated across both classes, and although the instructors were different for the two courses, the exact same material was delivered. This material included trendline theory and application examples in engineering and business fields. The

content of the slides and assessment was adapted from Evans (2013), which was used as the analytics course text for the business students, and Budny (2014), which was the text for the engineering students. Student mastery and understanding of the topic were assessed via a homework assignment that was the same for both groups.

All students in this study took traditional lecture based sections, taught live by the professor. The goals of the engineering course were exposure to basic analytical, programming design, graphical, and problem solving skills, as well as problem solving using various computer tools. Major topics of the course included basic UNIX commands, HTML and MATLAB programming, linear algebra, matrix operations, and spreadsheet fundamentals. The business course focused on using data to support decision making and using project management techniques to implement change. Those course objectives addressed using standard business spreadsheet software to summarize and analyze data and build decision models. Major topics covered in the business course included work breakdown structures, Gantt Charts, network diagrams, descriptive charts and graphs, histograms, predictive models, decision trees, and the newsvendor problem.

Students were given an individual homework assessment, which followed the in-class lecture. This assignment prompted the students to do the following tasks in Microsoft Excel: (1) test and determine a trendline of best fit; and (2) develop a predictive profit model. After the students submitted their individual homework assessment, they were directed to complete an online survey using an identification number to facilitate anonymity. The survey assessed motivation and attitude towards the analytics topics by including the established questions from the MUSIC[®] Model of Academic Motivation. The timing of the assessment and survey was at the end of the module on Excel and analytics for each group. For the engineering students, this was approximately week 4 of the semester, as their course later included UNIX, HTML, and MATLAB. For the business students, this was the end of the semester, as the module on analytics began after the midterm. The timing allowed students to reflect on their experiences learning analytics; reflection is encouraged by Jones (2015b).

3.2. Survey and Assessment Instruments

The survey was organized into three parts: (1) questions related to demographics, including age, gender, ethnicity, and degree program; (2) questions related to motivation and relationships among expectancies, values, and achievement which are adapted from Jones et al. (2010); and (3) questions adapted from the MUSIC[®] Model of Academic Motivation with the language adapted for "analytics" instead of "science"

(Jones 2017). We focus this study on responses provided in survey Sections (1) and (3). The literature has validated these sets of questions as predictions of motivation and learning (Jones and Skaggs 2012). All constructs in the MUSIC portion of the survey were measured using a six-point Likert scale ranging from strongly disagree to strongly agree. Although the survey is well established, we performed reliability estimates. Selected questions from the survey appear as Appendix A.

Each construct in the MUSIC® Model of Academic Motivation is defined in degrees by Jones (2017). The Empowerment construct is the degree to which the students believe they have control over their learning environment. Empowerment is based on 5 items ($\alpha = 0.910$), such as “I had control over how I learned the course content,” “I had the opportunity to decide for myself how to meet the course goals,” and “I had the freedom to complete the coursework my own way.” Usefulness is the degree to which students believe the course work is useful to their future. This construct is based on 5 items ($\alpha = 0.950$), such as “in general, the coursework was useful to me,” “the coursework was beneficial to me,” and “I found the coursework to be relevant to my future.” Success is the degree to which students believe they can succeed in the course work. The construct is based on 4 items ($\alpha = 0.886$), such as “I was confident that I could succeed in the coursework,” and “I was capable of getting a high grade in this course.” Interest is the degree to which the student believes that the instructional methods and course are interesting and enjoyable. Six items measure this item ($\alpha = 0.925$), such as “the coursework was interesting to me,” “the coursework held my attention,” and “I enjoyed completing the coursework.” The last construct is Caring, which is the degree to which students believe that the instructor cares about student success in the coursework and general well-being. Caring includes six items ($\alpha = 0.879$) such as “the instructor cared about how well I did in this course,” “the instructor was respectful of me,” “the instructor was friendly,” and “I believe that the instructor cared about my feelings.”

We added Attitude as an additional construct in the survey, defined as the degree to which the student has positive or negative feelings towards analytics coursework. One question asked for personal attitude towards analytics, with options of positive and negative. In addition, we asked students to provide an open-ended response for the reason for their attitude towards analytics. We then analyzed these open-ended responses using qualitative methods to understand why students had a positive or negative attitude towards statistics and analytics.

The homework assignment, or assessment, was initially graded for the course, and the grades were incorporated into the students’ final courses grades. A teaching assistant graded the engineering students for the

class grade, while the business professors graded their students. To ensure consistency, we then used an independent grader to reevaluate the assessments for every student in all classes on a 65 point scale with a rubric. For the independent grader, names were removed from the assignment and replaced by the survey ID number. Those scores were used in our analysis, with validity to the original class scores confirmed via correlation analysis. Specifically, $r = 0.751$ for the engineering teaching assistant and the independent grader; $r = 0.847$ for the first business professor and independent grader (61 students); and $r = 0.660$ for the second business professor and independent grader (33 students). These correlations are considered acceptable, based on Fleiss (1971). The assessment and rubric are included as Appendices B and C.

4. Model and Results

Figure 1 presents a model of our research approach.

4.1. Research Question 1: Differences in Motivation

Based on the analysis shown in Tables 1–3 we conclude that while students with positive attitudes have higher motivation and performance in general (Table 1) and motivation influences performance for those with a positive attitude (Table 2), there are few differences between engineering and business students’ motivation towards analytics, except in the Caring construct, despite significant differences in performance on the assessment between these two groups (Table 3). We discuss in detail below.

Of the 131 students who participated in the survey and assessment, 104 reported a positive attitude towards data analytics and 27 reported a negative attitude. To examine differences in motivation based on attitude, comparison of means tests were run for each MUSIC component as well as the assessment, comparing means of positive and negative students. Because the number of students with a negative attitude is fewer than 35, Kolmogorov-Smirnov normality tests were run on this sample: Usefulness and Success were both significant, implying nonnormality. As a result, two sample t tests were used for Empowerment, Interest, Caring, and the assessment, and Mann-Whitney tests were used for Usefulness and Success. Table 1 shows the results of these tests, for the five MUSIC

Figure 1. Research Model

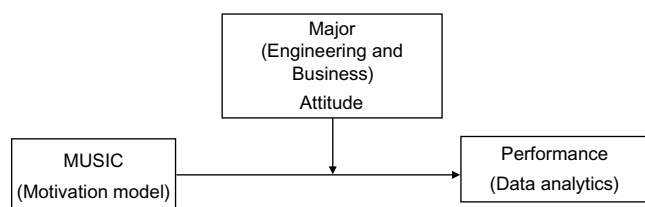


Table 1. Comparison of Means for Students with Positive vs. Negative Attitudes Towards Analytics Regardless of Major; Asterisks Denote Significance

Component	M		σ		Mean difference	t or W	df	Two-tailed p
	Positive N = 104	Negative N = 27	Positive N = 104	Negative N = 27				
Empowerment	4.408	3.86	0.904	1.13	0.548	2.34	35	0.025**
Usefulness	4.6	4				7,524.5		0.0002***
Success	5	4.25				7,478.5		0.0005***
Interest	4.16	3.49	0.937	1.28	0.673	2.55	33	0.016**
Caring	4.867	4.38	0.7	1.04	0.49	2.31	32	0.028**
Assessment	47.1	34.3	16	16.2	12.79	3.66	40	0.001***

components as well as the total assessment score. All MUSIC components are significant, implying a difference in motivation between students with positive and negative attitudes towards data analytics. There is also significant difference in assessment performance between students with positive and negative attitudes regardless of major.

For students with a positive attitude towards data analytics, a regression with the MUSIC components as predictors and the assessment score as the response is significant. Furthermore, Success and Caring are also significant in that model, implying a clear influence on assessment performance based on motivation for positive attitude students. The R^2 for such a regression is low, so a prediction of MUSIC constructs on assessment cannot be concluded, regardless of attitude. Such influence relationships are not concluded for students with a negative attitude towards data analytics, as the regression model is not significant for this group. Results are shown in Table 2.

We then considered students in each major. Mean values for the MUSIC components as well as the assessment score, with all students grouped by major, are presented in the first portion of Table 3. The comparison of means results shows that only Caring and the assessment differences are significant, indicating: (1) the business students perceived Caring to be higher than the engineering students; and (2) engineering students performed significantly better on the assessment.

Table 2. Regression Results with MUSIC Model Components as Predictors of Assessment Scores by Attitude; Asterisks Denote Significance

	Positive	Negative
	N = 104	N = 27
Empowerment	0.716	0.179
Usefulness	0.957	0.375
Success	0.030**	0.701
Interest	0.852	0.180
Caring	0.006***	0.355
Regression significance	0.023*	0.604
R^2	0.1228	0.1493

A deeper dive into this data was done by grouping students by attitude and major. Results of those tests are presented in the remaining portion of Table 3. In this case, we see significant differences based on attitude of business students for all five MUSIC components. Significant differences also exist for Empowerment, Interest, and Caring between engineering and business students with positive attitude, as well as Success between engineering and business students with a negative attitude towards statistics and data analytics.

4.2. Research Question 2: Contribution of Motivation to Performance

For this question, we conclude that although assessment scores may not depend on motivation alone, there is some relationship between assessment scores and motivation as measured by the MUSIC model when moderated by major.

Again, referencing Table 3, we present difference in means tests for the total assessment score for all engineering students versus all business students, then broken down by major and attitude. Significant tests include assessment scores for engineering versus business students with positive attitudes as well as engineering versus business students with negative attitudes. Tests on students in the same major with different attitudes did not show significance.

To further examine the effect of motivation scores on performance, we performed regression analyses with the five MUSIC components as predictors and the assessment scores as responses, breaking up the data by attitude and major. Results are summarized in Table 4; the regressions are not significant. Each of the five MUSIC components, when considered in addition to the other components, have no significance in explaining the assessment score for all engineers as well as for business students with a negative attitude. For all business students, Usefulness and Success have significance in explaining the assessment score. For students with a positive attitude, Usefulness has significance for engineering students, and Interest has significance for business students. The sample size of engineers with a negative attitude ($N = 5$) is not large enough for a full regression analysis.

Table 3. Comparison of Means for MUSIC Model Components and Assessment Scores by Major as Well as by Major and Attitude; Asterisks Denote Significance

Group 1	Group 2	Component	M		σ		Mean difference	<i>t</i> or <i>W</i>	<i>df</i>	Two-tailed <i>p</i>
			Group 1	Group 2	Group 1	Group 2				
All engineering <i>N</i> = 63	All business <i>N</i> = 68	Empowerment	4.137	4.44	0.886	1.04	−0.305	−1.81	128	0.072
		Usefulness	4.33	4.36	0.792	1.21	−0.026	−0.15	116	0.885
		Success	4.766	4.618	0.64	0.937	0.148	1.06	118	0.289
		Interest	3.929	4.11	0.914	1.16	−0.179	−0.99	125	0.326
		Caring	4.585	4.934	0.7	0.861	−0.349	−2.56	126	0.012**
		Assessment	57.06	32.8	7.05	14.7	24.23	12.16	97	<0.001***
Engineering with positive attitude <i>N</i> = 58	Engineering with negative attitude <i>N</i> = 5	Empowerment	4.155	3.92	0.906	0.626	0.235	0.77	5	0.474
		Usefulness	4.414	3.36	0.72	1.02	1.054	2.25	4	0.087
		Success	4.784	4.55	0.658	0.326	0.234	1.38	7	0.209
		Interest	3.983	3.3	0.863	1.35	0.683	1.11	4	0.327
		Caring	4.615	4.233	0.716	0.346	0.382	2.11	7	0.073
		Assessment	57.57	51.2	6.75	8.7	6.37	1.6	4	0.186
Business with positive attitude <i>N</i> = 46	Business with negative attitude <i>N</i> = 22	Empowerment	4.726	3.85	0.803	1.23	0.881	3.07	29	0.005***
		Usefulness	4.8	4				1,860.5		<0.001***
		Success	4.902	4.023	0.791	0.954	0.879	3.75	35	0.001***
		Interest	4.384	3.53	0.987	1.3	0.854	2.73	33	0.010***
		Caring	5.185	4.41	0.535	1.15	0.776	3.01	25	0.006***
		Assessment	34	30.5	14.5	15.1	3.46	0.89	40	0.377
Engineering with positive attitude <i>N</i> = 58	Business with positive attitude <i>N</i> = 46	Empowerment	4.155	4.726	0.906	0.803	−0.571	−3.4	100	0.001***
		Usefulness	4.414	4.713	0.72	0.974	−0.299	−1.74	80	0.086
		Success	4.784	4.902	0.658	0.791	−0.118	−0.81	87	0.420
		Interest	3.983	4.384	0.863	0.987	−0.401	−2.18	89	0.032**
		Caring	4.615	5.185	0.716	0.535	−0.57	−4.64	101	0.00***
		Assessment	57.57	34	6.75	14.5	23.61	10.18	60	<0.001***
Engineering with negative attitude <i>N</i> = 5	Business with negative attitude <i>N</i> = 22	Empowerment	3.92	3.85	0.626	1.23	0.075	0.19	12	0.849
		Usefulness	3.2	4				60		0.553
		Success	4.55	4.023	0.326	0.954	0.527	2.11	20	0.048**
		Interest	3.3	3.53	1.35	1.3	−0.23	−0.35	5	0.742
		Caring	4.233	4.41	0.346	1.15	−0.176	−0.61	22	0.550
		Assessment	51.2	30.5	8.7	15.1	20.7	4.1	10	0.002***

Table 4. Regression Results by Major and Attitude; Asterisks Denote Significance

	All students		Positive attitude		Negative attitude
	Engineers <i>N</i> = 63	Business <i>N</i> = 68	Engineers <i>N</i> = 58	Business <i>N</i> = 46	Business <i>N</i> = 22
Empowerment	0.151	0.435	0.141	0.658	0.212
Usefulness	0.185	0.041**	0.084*	0.195	0.117
Interest	0.195	0.337	0.181	0.044**	0.160
Success	0.633	0.058*	0.598	0.104	0.212
Caring	0.759	0.205	0.760	0.238	0.666
Regression significance	0.131	0.143	0.121	0.163	0.354
<i>R</i> ²	0.1352	0.1218	0.1503	0.1731	0.2725

5. Qualitative Analysis on Student Attitudes

Because attitude is found to be significant with regard to student motivation, we analyzed the survey open response item in which students provided an explanation as to why they selected a positive or negative attitude towards data analytics.

The qualitative data analysis focused on categorizing and describing participants' attitude toward data analytics. We coded the responses using a priori and emergent (or inductive) coding techniques (Patton 2002). We developed the codebook to describe student

attitude using a team-based approach (Carey et al. 1996) that involved specifying each code, the contextualized definition, the inclusion criteria, and example quotes (MacQueen et al. 1998). NVivo, a software package for qualitative data analysis, was used to support our study.

The development of the codebooks used multiple coders and involved one researcher whose primary responsibility was to create, update, and revise the codebooks, and a second researcher to establish inter-coder agreement. The second researcher was also the independent grader for the student assessments. First-stage structural coding (MacQueen et al. 1998), was

used to broadly map responses from business and engineering students to categories.

First-cycle inductive coding was applied to the textual responses for students who answered the positive attitude or negative attitude question as well as the open response item. Second-cycle coding involved using the second coder to independently code the responses by applying the codebook and the NVivo software package. The results of using multiple coders involved the identification of detailed codes in each category and the updated codebook. For the final cycle, both researchers coded the participant responses, applying the updated codebook, with inconsistencies noted, discussed, and resolved. Resolution involved discussion of a particular segment that was coded differently by each researcher until a consensus was reached about where it should be placed.

We used inter-coder agreement tests to ensure reliability and performed inter-rater reliability checks using NVivo after the coding scheme was finalized. Cohen's Kappa statistics (Cohen 1960) were calculated by dividing the number of agreements by the total number of responses. Inter-rater reliability averaged 0.87 between coders, where values greater than 0.75 are considered excellent agreement (Fleiss 1971).

Responses were then coded to indicate if the respondent identified as a business or engineering major. Six main themes emerged from the business and engineering student response sets. Individual responses were coded as "enjoyment," "future use," "ability," "usability," "technology," and "past or present experience." Table 5 lists the codes, subcodes, and definitions.

5.1. Enjoyment

The most common type of response for students was categorized as a form of the application or use of data analytics. In the free form text survey response, approximately 20% of students in this study expressed an enjoyable or positive outlook on data analytics.

5.2. Future Use

General perceptions of future use included analysis of large data sets, use in forecasting or predictions, understanding and making sense of information, and decision making. For example, students responded:

"I think it's a very beneficial way to get a lot of data in a condensed way that still makes sense." (Business major)
"Statistics and data analytics gives useful information that suggests important conclusions and supports decision making." (Business major)
"Data analytics and statistics can be useful for solving various problems in a relatively simple way." (Engineering major)

Table 5. Codebook Codes and Definitions for Qualitative Analysis of Student Open Ended Responses

Code (subcode)	Definition
Future use (positive, negative, predictive)	Future use or applications in engineering and/or business fields or future careers.
Usability (positive, negative)	General usefulness or applicability of data analytics techniques, findings, or approach. Also includes the negative case, where data analytics is identified as not useful.
Ability (positive, negative)	Self-identified ability in mathematics, statistics, or a related field to data analytics. Also includes the negative case, i.e., self-identified lack of ability in these areas.
Enjoyment (negative, positive)	Identification of the course material or material related to data analytics as enjoyable, or the negative case as not enjoyable.
Technology (comfort with Excel, usefulness of Excel)	Use of software, e.g., Excel, in analyzing data, could have positive or negative perceptions.
Past or present experience (positive, negative, course instructor)	Identified experience in an educational context and related to statistics, math, etc. Experience could be labeled as positive, negative, neutral.

"It helps determining a basic idea of what's going on with the data gathered or given." (Engineering major)

Other respondents indicated more specific applications in the business or engineering disciplines.

"There is real world use for it, especially with running a business successfully." (Business major)
"Helps in many ways business related like analyzing cost, demand and supply." (Business major)
"Many of our techniques in engineering involve ignoring minute quantities, such as friction, therefore we need statistics to present accurate information." (Engineering major)

Not surprisingly, business and engineering majors saw the application in their respective fields. The responses given by students did not show any cross-over with respect to application, such as engineering students indicating the usefulness of data analytics for business applications.

5.3. Ability and Challenging or Difficult

Ability in mathematics-related fields was a more common response for engineering majors who indicated a positive attitude towards data analytics. Very few engineering majors indicated a negative attitude, and only one response identified it as challenging or difficult.

Positive:

"It is easy." *"I like how easy statistics is to understand."*
"Math oriented person." (Engineering majors)

Negative:

"I find it very complicated and confusing. All the input has to be exactly correct." (Engineering major)

Conversely, business majors were less likely to explain their positive or negative attitude for their quantitative skills ability. They indicated that they found data analytics challenging or difficult for positive and negative attitudes toward data analytics. The challenging or difficult nature they identified was linked to enjoying or valuing the subject (positive attitude) and perceived lack of ability (negative attitude).

Positive: *"Difficult and frustrating using excel this way but is very useful."* (Business major)

Negative: *"I am bad at Math!!"* (Business major)

The text responses, or qualitative data, from business and engineering students about their attitude toward or perceptions of data analytics support the findings from our quantitative analysis. Based on students' perceptions of applicability and their identified major, more business students indicated that data analytics would be useful to their career or future endeavors. Engineering students saw the value of data analytics more generally or in technical applications. The responses coded as "ability" and "future use" also support the finding that engineering students will be more successful in the course. Engineering majors were more likely to respond that they identified a strong ability in the mathematical disciplines, where business majors were more likely to identify data analytics as challenging or difficult.

5.4. Technology (Comfort with Excel, Usefulness of Excel)

The technology code emerged from participant responses related to the technology used in data analysis, i.e., Microsoft Excel. Engineering and business students, who identified Excel in their responses, held positive or negative perceptions of Excel and its application. Sample responses, highlighted below, show students' perceptions of Excel as a good technology to analyze and understand data analytics.

Positive responses to the technology:

"Analysis is simplified greatly through the use of excel." (Engineering major)

"Tools such as Excel can be of great use when analyzing large amounts of data." (Engineering major)

"Problem solving with excel is very helpful." (Business major)

"I have recently learned how to use Excel for all of these functions which has increased my understanding and ability along with ease in using." (Engineering major)

Some students, from engineering and business majors, identified the technology as a more negative factor for them as it related to data analytics.

Negative responses to the technology:

"Sometimes them can be hard to duplicate in Excel." (Business major)

"I am not very interested in computers." (Engineering major)

5.5. Past or Present Experience

Some participants identified experiences (mostly), in an educational context, as a factor in their current attitude. Responses that focused on a past or present experience were identified as unfavorable or enjoyable. Example experience-based responses attributed the unfavorable experience to previous instructors, and the more favorable responses were attributed to previous statistics courses.

"I had a bad Stats Teacher." (Business major)

"The statistics professor I had was awful and was not helpful to the students. I found that other professors that are helpful make it easier to understand." (Business major)

"I took AP stat in high school and I liked the course." (Engineering major)

"I enjoyed statistics in high school." (Engineering major)

6. Implications and Future Work

Our goals with this research have been to explore differences between engineering and business students with respect to motivation and performance on analytics topics and assignments. Although we conclude that engineering students perform better on analytics assignments than business students, we cannot conclude that motivation alone is the reason for that difference; major may play a part. Although we identified influence, there was little significance between MUSIC constructs for the two groups. However, attitude plays a role, as we find a significant difference in motivation between students with positive and negative attitudes towards data analytics.

The established literature shows a connection between attitude and self-efficacy. Future work will focus on the self-efficacy constructs in our survey and exploring relationships between students' self-efficacy and performance on analytics.

As shown in Table 3, the Caring construct in the MUSIC® Model of Academic Motivation was higher for the business students. This could be a result of the smaller class sizes in the business school. In addition, although we were careful to ensure that all three instructors used the same PowerPoint lecture notes and gave the same assignment for the assessment, we did not evaluate potential differences in instructor teaching styles. We recognize this as a limitation of the study, as subtle differences could impact student responses to the survey as well as the assessment scores.

7. Suggestions for Business and Engineering Educators

We can conclude that the most effective approach to teaching analytics differs for engineering and business students. While engineering students tend to perform better on analytics topics than business students regardless of attitude, business students can be

influenced towards a positive attitude and provided stronger motivation to perform better. Instructors must demonstrate the importance and relevance of the topic to business students and encourage them to have a positive attitude by showing a caring attitude and confidence in students' abilities to perform well. Doing so may increase motivation and interest in learning analytics.

Because we found the Caring construct to be significantly different between engineering and business students, we note some generalities about this construct that may be significant to those teaching analytics to business students. In general, caring is predicated on action (Ellerbrock et al. 2015). Instructors should provide a sense of support and establish a connection with students. Caring instructors demand academic excellence from each student (Ellerbrock et al. 2015), and examples of caring include communicating that students are capable of doing well in class and providing sufficient help and support when necessary. Meyers (2009) identified the caring dimension as an integral part of teaching and learning in college. Abrami et al. (1997) found the "personal role" of professors to be important to students, specifically addressing professors' concern for them and fostering interaction. Often instructors do not interact with students, which can be perceived as noncaring. Studies have shown that rapport or interaction between students and faculty is associated with greater student enjoyment of the class, improved attendance, and increased study time (Benson et al. 2005). Some suggestions to increase interaction would be to use humor in class, address students by name, converse with students before class, ask questions to solicit different viewpoints, and praise students (Gorham 1988, Edwards and Edwards 2001).

Previous studies have shown a direct link between efficacy and performance (Pajares 1992, Hutchinson 1993); this study specifically highlighted the effect of positive attitude on data analytics performance. In engineering courses, large class sizes may obscure students' perceptions that the instructor cares about their performance and well-being. Engineering instructors can leverage students' positive attitudes toward analytics to enhance performance in their courses. We hope this research provides engineering and business educators further insight into improving teaching and student learning of analytics.

Acknowledgments

We thank Brittany Mattheu for her assistance as our independent grader/coder and Rana Rassipour for her assistance with data collection.

Appendix A. Survey

The survey contained three major sections: (1) demographics questions, (2) questions adapted from Jones et al. (2010), and

(3) questions adapted from Jones (2017). Below is a sampling of our questions.

Part 1: Demographics (included in their entirety)

Question 1. What is your age range?

- 18–25
- 26–35
- 36–45
- 46+

Question 2. What is your gender?

- Male
- Female

Question 3. What degree level are you presently registered in?

- Undergraduate
- Graduate
- Non-degree seeking student

Question 4. What is your ethnicity?

- African/American
- Asian
- Caucasian
- Hispanic
- Other

Question 5. What is your field of study?

- Business
- Engineering
- Other

Question 6. Where have you taken your most recent previous math course?

- Current university
- Another 4 year university
- Community College
- High School

Note that for this survey "data analytics" is defined as using trendlines, statistics, and other quantitative methods to analyze data with computer tools such as Microsoft Excel.

Question 7. What is your attitude towards statistics and data analytics?

- Positive
- Negative

Question 8. Please provide a reason for your attitude below:

Part 2: Questions adapted from Jones et al. (2010)

Those questions are not included here, as they were not used in this analysis. However, the questions modified the language to include "analytics" courses, instead of traditional STEM fields as used in the original questions.

Part 3: Questions adapted from Jones (2017)

The 26 questions from the MUSIC® Model of Academic Motivation were then presented, with the following instruction:

Please rate the items in this section using the following scale (6 point scale: strongly disagree to strongly agree).

The questions from Jones (2017) began with "The coursework held my attention" and ended with "I had flexibility in what I was allowed to do in this course."

Appendix B. Assessment

Problem 1 (Adapted from Budny 2014)

Given below is a table containing four sets of experimental data. Enter these data into an Excel spreadsheet and then

Table B.1. Data for Problem 1 Budny (2014)

x	Data set 1	Data set 2	Data set 3	Data set 4
0.00	2.00	0.00	−8.00	58.00
0.50	1.60	0.90	1.00	55.00
1.00	1.50	3.00	−6.00	45.00
1.50	0.90	6.00	−1.00	30.00
2.00	0.70	10.40	1.00	10.00
3.00	0.40	20.00	2.10	−41.00
4.00	0.27	40.00	3.90	−102.00
5.00	0.18	55.00	6.00	−167.00
6.00	0.10	65.00	8.00	−230.00
7.00	0.00	100.00	10.00	−285.00
8.00	0.04	120.00	12.00	−326.00
9.00	0.02	160.00	14.00	−347.00
10.00	0.00	190.00	16.00	−342.00

prepare individual plots of each set of data (vs. the original x data) on separate sheets in your workbook. Be sure to give each plot a title, x - and y -axis labels, and a legend. Use the x - y scatter plot option without connecting the points.

Examine the plots and decide which fit is appropriate:

- Linear $y = ax + b$ (relationship appears linear when plotted using both a normal x and normal y scale)
- Exponential $y = ae^{bx}$ (relationship appears linear when the y data are plotted on a log scale)
- Power $y = ax^b$ (relationship appears linear when both the x and y data are plotted on a log scale)
- If none of the above appear as a best fit, use a polynomial to fit the data.

Assume the data is experimental and will not fit any relationship exactly. Once you think you have identified the

appropriate relationship for a given set of data, use the trendline feature in Excel to add the trendline for the best fit. Select the appropriate options and be sure to display both the equation and r -squared value. Remember that both the exponential and power relationships require that data values of less than or equal to zero be filtered because the log of a nonpositive number is undefined. These data may need to be removed (filtered) from your analysis.

If the data are best fit with an exponential relationship (semi log), then also plot the natural log of y versus x . That is, you should create another column of data ($\ln y$) and have two plots. Add the linear trendline displaying the equation and r -squared values to the second plot.

If the data are best fit with a power relationship (log log), then also plot the natural log of y versus the natural log of x . That is, you should create two additional columns of data ($\ln x$ and $\ln y$) and have two plots. Add the linear trendline displaying the equation and r -squared values to the second plot.

Problem 2 (Adapted from Evans 2013)

A manufacturer of mp3 players is preparing to set the price on a new model. Demand (D) is thought to depend on the price (P) and is represented by the model:

$$D = 2,000 - 3P$$

The accounting department estimates that the total costs (C) can be represented by

$$C = 5,000 + 4D$$

Develop a model for the total profits (Revenues minus Costs) and represent it on an Excel spreadsheet. Use a table and a graph with \$ on the y -axis and Demand on the x -axis to find the price at which profit is maximized.

Appendix C. Scoring Rubric

	Possible
<i>Problem 1: Data set 1 (Exponential Fit)</i>	
Data plotted on scatter plot with title, axis labels, and points NOT connected	4
Exponential trendline shown on plot with both fit equation and R^2 value displayed	3
Data points with y values less than or equal to zero are filtered or removed	2
$\ln(y)$ calculated for each data point	2
$\ln(y)$ vs. x on second scatter plot with title, axis labels, and points not connected	4
Linear trendline with fit equation and R^2 value displayed on plot of $\ln(y)$ vs. x	3
<i>Problem 1: Data set 2 (Power Function)</i>	
Data plotted on scatter plot with title, axis labels, and points NOT connected	4
Power function trendline shown on plot with both fit equation and R^2 value displayed	3
Data points with both x and y values less than or equal to zero are filtered or removed	2
$\ln(x)$ and $\ln(y)$ calculated for each data point	2
$\ln(y)$ vs. $\ln(x)$ on second scatter plot with title, axis labels, and points not connected	4
Linear trendline with fit equation and R^2 value displayed on plot of $\ln(y)$ vs. $\ln(x)$	3

Appendix C (Continued).

	Possible
<i>Problem 1: Data set 3 (Linear Fit)</i>	
Data plotted on scatter plot with title, axis labels, and points NOT connected	4
Linear function trendline shown on plot with both fit equation and R^2 value displayed	3
<i>Problem 1: Data set 4 (Polynomial Fit)</i>	
Data plotted on scatter plot with title, axis labels, and points NOT connected	4
Polynomial trendline shown on plot with both fit equation and R^2 value displayed	3
<i>Problem 2</i>	
Data organized to show profits (price, demand, revenues, costs, profits)	4
Data is correct	4
Graph shows total profits	4
Correct price is found that maximizes profits	3
TOTAL	65

References

- Abrami PC, d'Apollina S, Rosenfield S (1997) The dimensionality of student ratings of instruction: What we know and what we do not. Perry RP, Smart JC, eds. *In Effective Teaching in Higher Education: Research and Practice* (Agathon, New York).
- Baillie C, Fitzgerald G (2000) Motivation and attrition in engineering students. *Eur. J. Engrg. Ed.* 25(2):145–155.
- Bandura A (1997) *Self-Efficacy: The Exercise of Control* (Freeman, New York).
- Benson TA, Cohen AL, Buskist W (2005) Rapport: Its relation to student attitudes and behaviors toward teachers and classes. *Teaching Psych.* 32(4):237–239.
- Besterfield-Sacre M, Atman C, Shuman LJ (1997) Characteristics of freshmen engineering students: Models for determining student attrition in engineering. *J. Engrg. Ed.* 86(2):139–149.
- Brookshire RG, Palocsay SW (2005) Factors contributing to the success of undergraduate business students in management science courses. *Decision Sci. J. Innovative Ed.* 3(1):99–108.
- Budny D (2014) *Introduction to Engineering Analysis* (Stipes Publishing, Champaign, IL).
- Camm JD, Cochran JJ, Fry MJ, Ohlmann JW, Anderson DR (2015) *Essentials of Business Analytics* (Cengage Learning, Fairfield, CT).
- Carey JW, Morgan M, Oxtoby MJ (1996) Inter-coder agreement in analysis of responses to open-ended interview questions: Examples from tuberculosis research. *Field Methods* 8(3):1–5.
- Cohen J (1960) A coefficient of agreement for nominal scales. *Ed. Psych. Measurement* 20(1):37–46.
- Deci EL, Ryan RM (1985) *Intrinsic Motivation and Self-Determination in Human Behavior* (Plenum, New York).
- Edwards A, Edwards C (2001) The impact of instructor verbal and nonverbal immediacy on student perceptions of attractiveness and homophily. *J. Excellence in College Teaching* 12(2):5–17.
- Ellerbrock CR, Abbas B, Diccio M, Denmon JM, Sabella L, Hart J (2015) Relationships—The fundamental R in education. *Phi Delta Kappan* 96(8):48–51.
- Eren A (2009) Examining the teacher efficacy and achievement goals, as predictors of Turkish student teachers' conceptions about teaching and learning. *Australian J. Teacher Ed.* 34(1):69–87.
- Evans JA (2013) *Business Analytics: Models, Methods, and Decisions* (Pearson, Boston).
- Fleiss J (1971) Measuring nominal scale agreement among many raters. *Psych. Bull.* 76(1):378–382.
- Gorham J (1988) The relationship between verbal teacher immediacy behavior and student learning. *Comm. Ed.* 37(1):40–53.
- Grossman TA (2006) Integrating spreadsheet engineering in a management science course: A hierarchical approach. *INFORMS Trans. Ed.* 7(1):18–36.
- Hidi S, Renninger KA (2006) The four-phase model of interest development. *Ed. Psychologist* 41(2):111–127.
- Hutchinson GE (1993) Prospective teachers' perspectives on teaching physical education: An interview study on the recruitment phase of teacher socialization. *J. Teaching in Physical Ed.* 12(4):344–354.
- Jones BD (2009) Motivating students to engage in learning: The MUSIC model of academic motivation. *Internat. J. Teaching and Learn. Higher Ed.* 21(2):272–285.
- Jones BD (2010) An examination of motivation model components in face-to-face and online instruction. *Electronic J. Res. Ed. Psych.* 8(3):915–944.
- Jones BD (2015a) The MUSIC® model of academic motivation: Research. Accessed January 5, 2016, <http://www.themusicmodel.com/research>.
- Jones BD (2015b) The MUSIC® model of academic motivation: Guide to assessing the MUSIC Model components. Accessed January 16, 2015, <http://www.MotivatingStudents.info>.
- Jones BD (2017) User guide for assessing the components of the MUSIC® model of motivation. Accessed June 19, 2017, <http://www.theMUSICmodel.com>.
- Jones BD, Skaggs G (2012) Validation of the MUSIC model of academic motivation inventory: A measure of students' motivation in college courses. *Internat. Conf. Motivation, Frankfurt, Germany*.
- Jones BD, Paretti MC, Hein SF, Knott TW (2010) An analysis of motivation constructs with first-year engineering students: Relationships among expectancies, values, achievement, and career plans. *J. Engrg. Ed.* 99(4):319–336.
- MacQueen KM, McLellan E, Kay K, Milstein B (1998) Codebook development for team-based qualitative analysis. *Field Methods* 10(2):31–36.
- Meyers SA (2009) Do your students care whether you care about them? *College Teaching* 57(4):205–210.
- Ohland MW, Sheppard SD, Lichtenstein G, Eris Ö, Chachra D, Layton RA (2008) Persistence, engagement, and migration in engineering programs. *J. Engrg. Ed.* 97(3):259–278.
- Pajares MF (1992) Teachers' beliefs and educational research: Cleaning up a messy construct. *Rev. Ed. Res.* 62(3):307–332.
- Patton MQ (2002) *Qualitative Research and Evaluation Methods*, 3rd ed. (Sage, Thousand Oaks, CA).
- Popham WJ (2005) Students' attitudes count. *Ed. Leadership* 62(6):84–85.
- Santiago LY, Hensel RA (2012) Engineering attrition and university retention. *Amer. Soc. Engrg. Ed. Annual Conf., San Antonio, Texas*.
- Simons J, Vansteenkiste M, Lens W, Lacante M (2004) Placing motivations and future time perspective theory in a temporal perspective. *Ed. Psych. Rev.* 16(2):121–139.
- Singh G, Siddiqui K (2009) Microsoft Excel software usage for teaching science and engineering curriculum. *J. Ed. Tech. Systems* 37(4):405–417.
- Van Woensel T, Fisher ML, Fransoo JC (2010) Teaching retail operations in business and engineering schools. *INFORMS Trans. Ed.* 11(1):29–34.
- Wilder CR, Ozgur CO (2015) Business analytics curriculum for undergraduate majors. *INFORMS Trans. Ed.* 15(2):180–187.