

Introducing Students to Business Analytics: A Case Study

Faye X. Zhu*

Rohrer College of Business
Rowan University
Glassboro, NJ 08028, USA
Email: zhu@rowan.edu

Joel Rudin

Rohrer College of Business
Rowan University
Glassboro, NJ 08028, USA
Email: rudin@rowan.edu
*Primary and corresponding author

Received: 2022-09-30

Accepted: 2022-10-10

Published online: 2022-10-22

Abstract

Employer demand for business analytics skills is strong, yet most universities provide an inadequate amount of business analytics education. This paper describes and evaluates an introductory business analytics course required for undergraduate business management majors. It examines not only students' perceptions of teaching effectiveness and learning satisfaction from end-of-semester surveys but also student learning outcomes measured by the instruments for the program assurance of learning. Student evaluations were not generally favourable, which is unsurprising for the courses like this that require statistical analysis and quantitative skills. However, the measures of learning showed positive results as over three-quarters of the students' demonstrated satisfactory performance in using analytical tools and applying spreadsheet and optimization models. Perceptions were enhanced for students who held more positive impressions of the instructor and of the team-based assignments, who expected higher grades, and who were more interested in the subject of business analytics. The study suggests that measures of learning may provide a more accurate picture of the effectiveness of business analytics coursework than measures of reactions.

Keywords: business analytics, business education, learning, reactions.

1. Introduction

Business analytics is "a systematic thinking process that applies qualitative, quantitative, and statistical computational tools and methods to analyze data, gain insights, inform, and support decision-making" (Power et al., 2018, p. 51). Employer demand for business analytics skills is strong (Cegielski & Jones-Farmer, 2016), yet

most universities provide an inadequate amount of business analytics education (Phelps & Szabat, 2017).

This paper aims to describe and evaluate an introductory business analytics course required for undergraduate business management majors. Previous research has described business analytics coursework and has discussed student evaluations (e.g., Jeyaraj, 2019; Zhang et al., 2020). However, student evaluations are considered less valuable than learning assessments in measuring educational effectiveness because they do not always predict learning (Praslova, 2010). Therefore, this study contributes to the literature by not only describing a business analytics course, examining its student evaluations, and investigating factors associated with student reactions but also measuring the amount of learning that occurred.

The next section describes our course, Foundations of Analytics (FOA), followed by the discussion of the research methodology and presentation of the empirical results based on the data from the Spring 2022 semester when we were finally able to return to the classroom after two years of remote instruction. We conclude with suggestions for teaching and research.

2. The Foundations of Analytics Course

We developed an introductory business analytics course, Foundations of Analytics (FOA), as a required core course for our undergraduate business management major. The purpose is to provide students with the fundamental concepts of business analytics and increase their proficiency in analytics tools and techniques. The course uses a balanced approach to discuss business analytics from descriptive, predictive, and prescriptive perspectives (Evans, 2020). It covers database analytics, visualization, descriptive and inferential statistics, regression analysis, spreadsheet modeling, what-if analysis, and linear optimization. Two prerequisites are a calculus course and a statistics course. Grading was based on class participation, team-based assignments, and exams.

The FOA course was taught in a computer lab. It combines traditional lectures with hands-on data analysis exercises. Most hands-on activities use Excel tools; some visualization exercises use Tableau. The course emphasizes critical thinking and analytical skills and focuses on applications of analytical tools with convenient and user-friendly computer technologies.

Many management students taking FOA have relatively weak backgrounds in statistics and quantitative skills, and some lack basic Excel skills. Further, students are accustomed to traditional methods and venues of mathematical instruction, i.e., using formulas to do manual calculations instead of interpreting the results from computer

outputs. Some students would insist on using their calculators for assignments even though the instructor stated clearly that the problems must be solved using Excel tools.

3. Methodology

3.1. Measures of learning

We developed measures of learning in a hierarchical fashion, i.e., from the learning goal for the undergraduate management program to the learning plan for the course to the specific course learning outcomes to be assessed. Each required course covers at least one of the program's learning goals.

The program learning goal related to FOA is that students will be able to solve qualitative and quantitative managerial problems. The course learning goal is that students can use essential analytical tools and interpret the results for business decision-making. The two specific learning outcomes are: (1) students will be able to use essential analytical tools for data queries and descriptive analytics, and (2) students will be able to develop and apply spreadsheet and optimization models for decision-making.

Two sets of the instrument, each consisting of ten multiple choice questions, were developed to measure student learning in the FOA course. Those questions are embedded in the tests, and the assessment results are used to identify the weak area and develop an action plan for teaching improvement. Our target is that at least 80% of students will perform at or above the satisfactory level, defined as answering at least 70% questions correctly for each set of the questions. Notice that the assessment scores are different from student course grades. A course grade may consist of multiple components, e.g., class participation, teamwork, homework, etc. The measures of learning are all learning subject related.

3.2. Student reactions

We used two dependent variables to measure student reactions: perceived teaching quality and learning satisfaction. Perceived teaching quality asks students to rate the quality of instruction as it contributed to their learning. Learning satisfaction asks students if they are happy with what they learned in class. Both questions use a 5-point Likert scale, with 5 being the most favorable response.

We chose a single-item measure for both dependent variables because they appear unambiguous. The literature suggests that single-item measures may suffice for narrowly defined constructs (Bergkvist & Rossiter, 2007; Wanous et al., 1997). Examples of using single-item measures to assess constructs include life satisfaction

(Schimmack & Oishi, 2005), job satisfaction (Wanous et al., 1997), relationship intimacy (Aron et al., 1992), and self-esteem (Robins et al., 2001).

3.3. Independent variables

We selected independent variables from the Student Instructional Report II (SIR II) with modifications to fit the study. The SIR II is a nationally normed instrument for student evaluations developed by the Educational Testing Service (ETS). Many researchers have used SIR II in their studies (e.g., Carrol & Burke, 2010; Thornton et al., 2010; Young & Duncan, 2014). A study about the variability of this instrument can be found in Potter, Romeo, Bao, & Pritchard (2008).

SIR II covers teaching related items in course organization and planning, faculty/student interaction, assignment, exam, and grading, and supplemental instructional methods. Student related items include perceive course outcomes, study effort, involvement, course difficulty, workload, and background information (e.g., gender, class level). All the questions use a five-point Likert scale. Students indicate to what extent they agree or disagree with the statements. We examined the effects of these variables on student reactions.

3.4 Sample data

We collected data from three sections of the FOA course at the end of the spring semester of 2022. This semester marked our return to in-class instruction after two years of remote teaching. The same instructor taught all three sections. Participation in the survey was optional, and there was no penalty for non-participation. Sixty usable responses were collected from a total enrollment of 77 students, with a 78 percent response rate. The final sample included 43 males (71.7%) and 17 females (28.3%) and had 25 third-year students (41.7%) and 35 fourth-year students (58.3%).

3.5 Methods of data analysis

Descriptive statistics was used to summarize the results of learning outcomes. Principal component analysis (PCA) was used to identify the smallest number of underlying dimensions that explain independent variables. Multiple regression analyses were performed to examine the effects of predictors (including the components identified from PCA and student background variables) on perceived teaching effectiveness and learning satisfaction.

4. Results

4.1 Descriptive statistics for learning outcome

Student evaluations of the course were not very favorable. On the five-point scale, the mean for perceived teaching quality was 3.27, and the mean for learning satisfaction was 3.33. On the other hand, the assessment of learning outcomes showed evidence of success. 78% of students displayed satisfactory learning in using essential analytical tools for data queries and descriptive analytics, and 83% performed satisfactorily in developing and applying spreadsheet and optimization models. We could not match the results of learning assessments with student reactions for further analysis because the student surveys were collected anonymously.

4.2 Principal components analysis

Table 1 presents the final solution of the principal component analysis. The cutoff value of 0.7 for factor loadings was used following the sample size guidelines for significance suggested by Hair et al. (1995, p. 385). The Kaiser-Meyer-Olkin (KMO) measure of 0.779 and the $\text{sig} < 0.001$ for Bartlett's test indicated that the sampling is acceptable (Hair et al., 1995). The solution accounted for 78.8% of the total variance.

Four components were identified. Two are teaching-related, labeled as instructor/instruction and team assignments, and the other two are student-driven, labeled as motivation and enthusiasm. The literature varies on the minimum acceptable value for Cronbach's alpha, ranging from 0.6 (Tavakol & Dennick, 2011) to 0.7 (Ursacho et al., 2015). So, we consider these components to be acceptable. All the remaining variables have communality values above or close to the ideal value of 0.7 (Beavers et al., 2013).

It's interesting to notice that the team-related variables stood out in all trials in the grouping process. In contrast, all other teaching-related variables (e.g., course organization and planning, faculty/student interaction, supplementary instructional methods) overlapped in one group. This dimensionality problem may be due to confusion in students' minds regarding distinctions between instructor and instruction-related items.

Table 1

Principal component analysis

Components / Items	Cronbacha	Factor loading	Communality
I. Teaching-related			
Instruction/Instructor Eigenvalue=4.84, % of variance=40.40	0.892		
1. Instructor explanation of learning objectives & requirements		0.730	0.623
2. Effectiveness of hands-on exercises to support course contents		0.721	0.609
3. Instructor preparedness		0.892	0.819
4. Instructor approachability		0.849	0.826
5. Instructor responsiveness		0.855	0.776
Team assignments Eigenvalue=1.95, % of variance=16.26	0.891		
1. Enhanced my learning of course materials		0.895	0.886
2. Effective in helping me understare course materials		0.926	0.880
II. Student-driven			
Motivation: Eigenvalue=1.53, % of variance=12.75	0.865		
1. Interests in learning more about the subjects		0.920	0.764
2. Perceived high demand for data analytics skills		0.918	0.870
3. Perceived career benefits from course learning		0.769	0.865
Enthusiasm: Eigenvalue=1.13, % of variance=9.42	0.627		
1. Preparedness for each class meeting		0.860	0.805
2. Study effort in advancing learning		0.768	0.736
<ul style="list-style-type: none"> • Overall % of variance explained = 78.83 • KMO measure of sampling adequacy = 0.779 • Bartlett’s test of sphericity: Approx. Chi-Square = 398.68 & Sig. < 0.001 			

4. 3 Factors associated with perceived teaching quality

Table 2 shows the regression results with perceived teaching quality as the dependent variable. The regression factor scores obtained in SPSS were used in this analysis. The predictors included the four components identified from PCA and four student background variables.

Both instruction/instructor ($p < 0.001$) and team assignments ($p = 0.009$) significantly and positively associated students’ perceptions of teaching quality. Students with higher motivation, i.e., perceive career benefits from course learning and are interested in the subject, appeared to give higher teaching quality ratings ($p = 0.09$). The results showed no significant effect from enthusiasm ($p = 0.951$). Students’ preparedness for class and effort in their studies did not appear to affect teaching quality ratings.

Table 2
Regression analysis for perceived teaching quality

Predictors	B	S.E.	B	t	Sig.
Intercept	0.166	1.136		0.146	0.884
Instruction/Instructor	0.928	0.157	0.598	5.907	<0.001
Team assignments	0.252	0.092	0.258	2.726	0.009
Motivation	0.181	0.105	0.160	1.731	0.090
Enthusiasm	-0.008	0.138	-0.006	-0.061	0.951
Expected grade	0.032	0.152	0.019	0.209	0.835
Class level	-0.401	0.199	-0.176	-2.019	0.049
Working hours / week	-0.038	0.100	-0.032	-0.378	0.707
Gender	-0.142	0.234	-0.053	-0.608	0.546

- B=unstandardized coefficient; S.E.=standard error; β=standardized coefficient
- Adjusted R²=0.608; F=12.433; Sig. <0.001

4.4 Factors associated with learning satisfaction

Table 3 shows the regression results with learning satisfaction as the dependent variable. The regression factor scores obtained in SPSS were used in this analysis. The predictors included the four components identified from PCA and four student background variables. Both instruction/instructor ($p < 0.001$) and team assignments ($p = 0.005$) were significantly associated with learning satisfaction. Students who gave higher instructional ratings and felt positively about the effectiveness of team assignments appeared to be happier with their learning outcomes. No significant effects of self-motivation and enthusiasm on learning satisfaction were found. The perceived grade was the only variable out of the four student background variables positively associated with learning satisfaction ($p = 0.09$). Students who expected higher grades appeared to be happier with course learning outcomes. Interestingly, this variable did not have affect students' perception of teaching quality.

Table 3
Regression analysis for learning satisfaction

Predictors	B	S.E.	B	t	Sig.
Intercept	-1.353	1.202		-1.125	0.266
Instruction/Instructor	0.755	0.166	0.520	4.545	<0.001
Team assignments	0.286	0.098	0.313	2.924	0.005
Motivation	0.062	0.111	0.058	0.557	0.580
Enthusiasm	-0.088	0.146	-0.063	-0.601	0.550
Expected grade	0.277	0.161	0.180	1.726	0.090
Class level	-0.148	0.210	-0.069	-0.705	0.484
Working hours / week	0.061	0.105	0.056	0.581	0.564
Gender	0.299	0.248	0.119	1.208	0.233

- B=unstandardized coeff.; S.E.=standard error; β=standardized coeff.
- Adjusted R²=0.498; F=8.312; Sig. <0.001

5. Discussion

One interesting finding is the contrast between student reactions to the course, which were not very favourable, and impressive student learning. Although we did not conduct an entry test, we have no reason to believe that our students entered this class with solid statistical and quantitative foundations. Thus, we can confidently attribute their success in learning to what occurred in the classroom.

Business analytics relies heavily on statistical tools, yet students generally dislike statistics courses (Carrillo et al., 2018). Therefore, it is unsurprising that student evaluations of business analytics courses may be unfavourable. Although we would argue that learning is more important than student reactions because it enables students to apply business analytic tools and techniques on their jobs after graduation, achieving success on both sets of outcomes would be ideal. Our regression analyses may yield insights that can help achieve that goal.

Pedagogy covers various aspects of teaching, including teaching styles, course organization, supplementary instructional methods, feedback, assessment, etc. These components appear to have a combined effect on students' perception of teaching quality and learning satisfaction. Yet team assignments would stand out separately from these components. If students are happy with team members, working together would help enhance their learning experience and thus have a significant positive effect on their ratings of teaching quality and learning satisfaction. On the hand, teams having trouble getting all members together to do the assignments would feel frustrated, especially when the works count for a large portion of the grade. In this case, team assignments negatively affect students' perceptions of teaching quality and learning satisfaction. This finding provides the instructor with helpful information for teaching improvement, e.g., checking the progress of each team assignment before its due date and having some class time for team discussion, etc.

This study shows evidence that student self-motivation, e.g., interests in the subject matter and recognition of the demand for business graduates with BA skills, and positively affects their perceptions of teaching quality. The instructor may use more real-world applications in future classes to show the relevance and importance of data analytics in today's business world to promote student learning. This study does not find significant effects of enthusiasm, e.g., student preparedness for class meetings and study efforts, in advancing course learning.

Surprisingly, there appears to be no significant effect of expected grades on teaching quality ratings. A general assumption would be that the higher the predicted

grades, the higher the teaching quality ratings. However, the study found evidence that this variable positively affects student learning satisfaction.

The study does not find a significant effect of working hours on students' perception of teaching quality and learning satisfaction. One possible explanation may be that all the lecture notes and other class materials are accessible in Canvas and help those who need to self-study in different periods. A prior study also found no significant effect of the number of working hours on students' grades in an Accounting Information Systems course (Rodriguez et al., 2021).

6. Limitations and Suggestions for Research and Teaching

This exploration into the combining of learning and teaching styles has limitations. The sample of management students in one course at one university reduces the opportunity to generalize the results. The small sample size indicates that the scales should be interpreted with caution. Further, there are many conceptualizations of teaching style and quality, and alternative measures to assess perceptions of teaching style, approach, attribute, or technique may result in different findings.

Future research directions abound. For example, it would be helpful to replicate our results in future semesters to evaluate the effectiveness of interventions such as tutoring sessions. More case studies of business analytics coursework would also be beneficial, especially if they can supplement student reaction data with information on the learning success students have achieved.

Surveys of business analytics education may focus on degree programs rather than individual courses (Gorman & Klimberg, 2014; Zheng, et al., 2021). Today's managers must understand business analytics (Vidgen, et al., 2017). It may be beneficial to situate business analytics coursework within a popular undergraduate major, such as management, rather than restrict it to students who wish to specialize in this area. We would be happy to share our syllabi and assessment designs with interested colleagues upon request to assist this journey at other academic institutions.

References

- Aron, A., Aron, E., & Danny, S. (1992). Inclusion of other in self scale and the structure of interpersonal closeness. *Journal of Personality and Social Psychology*, 63(4), 596-612.
- Beavers, A.S., Lounsbury, J.W., Richards, J.K., Huck, S.W., Skolits, G.J., & Esquivel, S.L. (2013). Practical considerations for using exploratory factor analysis in educational research. *Practical Assessment, Research, and Evaluation*, 18(1), 6.
- Bergkvist, L. & Rossiter, J. (2007). The predictive validity of multiple-item versus single-item measures of the same constructs. *Journal of Marketing Research*, 44(2), 175-184.
- Carillo, K., Galy, N., Guthrie, C., & Vanhems, A. (2018). How to turn managers into data-driven decision makers: Measuring attitudes towards business analytics. *Business Process Management Journal*, 25(3), 553-578.
- Carrol, N. & Burke, M. (2010). Learning effectiveness using different teaching modalities. *American Journal of Business Education*, 3(12), 65-76.
- Cegielski, C., & Jones-Farmer, L. (2016). Knowledge, skills, and abilities for entry-level business analytics positions: A multi-method study. *Decision Sciences Journal of Innovative Education*, 14(1), 91-118.
- Evans, J. (2020). *Business Analytics*(3rd Ed), Pearson.
- Gorman, M. & Klimberg, R. (2014). Benchmarking academic programs in business analytics. *Interfaces*, 44(3), 329-341.
- Hair, J.F. Jr., Anderson, R.F., Tatham, R.L., Black, W.C. (1995). *Multivariate Data Analysis*(4th Ed), Prentice Hall.
- Jeyaraj, A. (2019). Pedagogy for business analytics courses. *Journal of Information Systems Education*, 30(2), 67-83.
- Phelps, A. & Szabat, K. (2017). The current landscape of teaching analytics to business students at institutions of higher education: Who is teaching what? *American Statistician*, 71(2), 155-161.
- Potter, G.C., Romeo, G.C., Bao, D.H., & Pritchard, R.E. (2008). Using standardized student evaluation instruments to measure teaching effectiveness in lecture/recitation mode classes. *Journal of College Teaching & Learning*, 5(3), 1-8.
- Power, D., Heavin, C., McDermott, J., & Daly, M. (2018). Defining business analytics: An empirical approach. *Journal of Business Analytics*, 1(1), 40-53.
- Praslova, I. (2010). Adaptation of Kirkpatrick's four level model of training criteria to assessment of learning outcomes and program evaluation in higher education. *Educational Assessment, Evaluation and Accountability*, 22(3), 215-225.
- Robins, R., Hendin, H., & Trzesniewski, K. (2001). Measuring global self-esteem: Construct validation of a single-item measure and the Rosenberg Self-Esteem Scale. *Personality and Social Psychology Bulletin*, 27(2), 151-161.

- Rodriguez, C., Maksy, M.M., & Shahid, N.U. (2021). An empirical investigation of factors related to student performance in accounting information systems. *International Journal of Business and Economics*, 6(2), 135-149.
- Schimmack, U. & Oishi, S. (2005). The influence of chronically and temporarily accessible information on life satisfaction judgments. *Journal of Personality and Social Psychology*, 89(3), 395-406.
- Tavakol, M. & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, 2(1), 53-55.
- Thornton, B., Adams, M., & Sepehri, M. (2010). The impact of students' expectations of grades and perceptions of course difficulty, workload, and pace on faculty evaluation. *Contemporary Issues in Education Research*, 3(12), 1-5.
- Ursacho, G., Horodnic, I., & Zait, A. (2015). How reliable are measurement scales? External factors with indirect influence on reliability estimators. *Procedia Economics and Finance*, 20(1), 679-686.
- Vidgen, R., Shaw, S., & Grant, B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research*, 261(2), 626-639.
- Wanous, J., Reicher, A., & Hudy, M. (1997). Overall job satisfaction: How good are single-item measures? *Journal of Applied Psychology*, 82(2), 247-252.
- Young, S. & Duncan, H. (2014). Online and face-to-face teaching: How do student ratings differ? *MERLOT Journal of Online Learning and Teaching*, 10(1), 70-79.
- Zhang, L., Cheng, F., & Wei, W. (2020). A foundation course in business analytics: Design and implementation at two universities. *Journal of Information Systems Education*, 31(4), 244-259.
- Zheng, Y., Hameed, T., Lavoie, R., & Sendall, P. (2021). An overview of business analytics programs across US business analytics schools. *Issues in Information Systems*, 22(2), 306-317.