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Delivering a Business Analytics Course Focused on Data Mining for Both Technical and Non-Technical Students

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ABSTRACT

The current study details the development of an undergraduate business analytics course that combines components of both active and experiential learning. The course offering is designed to expose students from different backgrounds to an intermediate-to-advanced level of business analytics. The course is unique in that it was designed to be appropriate for both "tech savvy" and non-technical learners—two groups who likely possess very different skill sets. The course incorporates high-level analytic techniques and algorithms that enhance decision-making and makes use of a business analytics platform called RapidMiner that includes embedded analytic frameworks, so learners do not require prior computer programming experience to be successful. Each course module incorporates different types of lab projects—including heavy usage of guided lab projects, self-paced problem-solving labs, and exam-based lab assessments—where students have multiple opportunities to practice building increasingly sophisticated experiences over time. Pre- and post-course surveys were used to assess course design, including student engagement, student learning, learning interest, and learning satisfaction. Quantitative analyses of course perceptions over time reveal that students, on average, report increases in engagement, satisfaction, and learning interest. Students demonstrate significant improvements in their understanding and overall attitudes toward business analytics, which appears to generate additional excitement about future exposure to business analytics as a subject of interest.

Keywords: Business analytics, Course development, Data mining, Experiential learning & education, Active learning

1. INTRODUCTION

The current big data environment in modern business operations is characterized by a set of key features, or the six "Vs" including volume, velocity, variety, volatility, veracity, and value (Zadeh et al., 2021). To manage the six Vs in an efficient and effective manner, data scientists across various types of organizations must not only demonstrate deep technical/quantitative skills but also possess the requisite knowledge to use business analytics to facilitate enhanced strategic planning and decision-making.

Many colleges and universities have been designing business analytics courses and programs to meet the expanding job market demand for graduates possessing adequate knowledge and skills to apply business analytics to the real world. Since business analytics is multidisciplinary, with a wide variety of perspectives regarding the preparation, analysis, understanding, and presentation of different types of business data, various academic institutions include their own "flavor" of business analytics offerings in their curricula. For example, certain educational programs may focus on providing broad-based business analytics courses to a general business student audience, with other programs offering technical course options for students who have stronger programming skills and better training in the application of technological solutions.

This study presents our efforts in developing an effective business analytics course targeting technical and non-technical and senior-level undergraduate students. The main goals of this study are: (1) to inform course development and delivery so that students can grasp advanced business analytics techniques and algorithms without the need for programming prerequisites, and (2) to hopefully generate excitement and interest in analytics as a future career path for a diverse set of students.

The current paper differs from most of the extant research on business analytics course design and development. Our study includes a systematic evaluation process using pre- and post-course student surveys to assess the effectiveness of course development efforts over time. On the other hand, much of the past work used end-of-semester course evaluation results or qualitative end-of-semester questions as proxy measures for effective course design. While this past work has added to overall understanding, our intention is to supplement the extant literature via a more robust study design.

The remaining sections of the paper are organized as follows. In Section 2, a literature review of past business analytics courses and program development efforts is presented. Specific details on our business analytics course design and development are provided in Section 3, with course assessment of learning support provided in Section 4. Section 5 concludes this paper with a detailed discussion of results, including study limitations and potential directions for future work.

2. LITERATURE REVIEW

2.1 Fundamental Theories: Experiential Learning Theory and Active Learning Theory

Two well-known, learning-related theories that are helpful in designing learning-centric business analytics courses are The (ELT) and active learning theory (ALT). When designing our course, these two theories were top of mind. Consequently, we used these fundamental theories to help organize course topics and develop hands-on lab activities where students can practice applying what they are learning.

ELT, as conceptualized by Kolb (1984), emphasizes a "learning by doing" mindset. Here, knowledge is internalized by learners through the "transformation of experience" (Kolb, 1984, p. 41). ELT conceptualizes learning as a four-stage process, including concrete experience and the willingness of the learner to be actively involved in the experience (McCarthy, 2010), reflective observation and the ability of a learner to reflect on the meaning of their experience (McCarthy, 2010), abstract conceptualization with the learner thinking about how to apply learned techniques (Itin, 1999; McCarthy, 2010), and active experimentation with the learner applying what has been learned from their experience to specific problems (Itin, 1999).

ALT asserts that "active learning" occurs when learners go beyond passive participation (e.g., watching, listening, and taking notes; Felder & Brent, 2009), and become experientially involved in the learning process using two-way communication (e.g., writing, discussing, and engaging in problem-solving; Romanow et al., 2020) and higher-ordered thinking (e.g., analysis of data, synthesis of information, evaluation of alternatives and self-reflection; Bonwell & Eison, 1991).

2.2 Literature on Business Analytics-Related Education

Today's Internet and computing technology has led to the generation of vast amounts of business data (i.e., "big data"), with the quantities of raw data increasing exponentially. The rich amount of information to be mined from these data could be very valuable for organizations as they seek to understand business operations and generate sustainable competitive advantages.

Business analytics is defined as "the use of data, IT, statistical analysis, quantitative methods, and mathematical or computer-based models to help managers gain improved insights about their business operations and make better and fact-based decisions" (Choi et al., 2017, p. 2). The field of business analytics is multidisciplinary in nature, requiring requisite knowledge of both business operations and data management. Business analytics connects different business domains together when applied to functional problems, including linking marketing, finance, human resources, etc.

In recent years, there has been a significant increase in the demand for business analytics solutions worldwide (Choi et al., 2017). To address the shortage of business analytics talent available in the job market, many universities are expanding analytics courses, certificates, minors, and major program offerings (Asamoah et al., 2017; Choi et al., 2017; Olson, 2018).

Information systems (IS) activities cascade across all other disciplines. Because of the bridging nature of IS in the business school, which aims to provide students with both technical skill backgrounds with business-specific knowledge, many of the business analytics courses and programs at US universities have been deployed by business IS departments, with complementary efforts made in the computer science and informatics domains as well.

A significant body of literature has been published on the development of classes and programs that prepare students to conduct business analytics activities in real-world companies. We examine this topic from multiple perspectives using different contextual settings.

2.2.1 Business Analytics Courses of Different Scopes. The extant literature on business analytics pedagogy includes ongoing discussions and insights on how to create effective standalone business analytics courses (Pomykalski, 2021; Yap, 2020; Zhang et al., 2020), as well as business analytics-oriented degree programs and certifications (Clayton & Clopton, 2019; Molluzzo & Lawler, 2015; Olson, 2018).

Regarding course-level business analytics design, Zhang et al. (2020) report the design and development of a business analytics class as an elective class for all business majors, whose purpose is to train students to conduct basic intermediate-level business analytics activities. The paper offers a thorough explanation of course design with detailed topic coverage and timelines, as well as sample assignments and hands-on labs. The study also demonstrates how the same course design was used at two universities in the US and Canada, with the effectiveness of the overall course design supported via positive student course evaluation scores.

In another recent study on business analytics course design, Yap (2020) focuses on designing visual analytics dashboard applications. A specific list of design methodologies is identified and used to guide the business analytics dashboard design, including redundant visual representations, clear layouts for input and output objects, colors for indicators, storytelling, visual synergy, and defining the scope of application and range of data. Case studies of four specific dashboard applications used in the class are described in detail.

Instead of designing and implementing a business analytics class from scratch, Pomykalski (2021) focuses on redesigning an existing traditional IS class into a more valuable business analytics course offering. Specifically, this paper discusses how a traditional systems analysis and design (SA&D) class is redesigned into an introductory-level business analytics class, with the goal of introducing students to the basic procedures and skills needed to perform effective business analytics. New learning objectives and skill-based priorities are identified and used as the basis for redesigning the class.

In addition to the design and demonstration of a single business analytics course, efforts to design a business analytics curriculum around a series of classes have also been addressed in existing literature. Molluzzo and Lawler (2015) describe the redesign of an IS curriculum with a business analytics concentration at Pace University. As an on-going effort, their paper describes a list of different courses to be included in the new curriculum and organizes these course offerings into three groups (i.e., initial concept, domain-specific, and enabling courses focuses on integration). In another effort to develop multiple business analytics courses at the University of Nebraska-Lincoln, Olson (2018) discusses in detail the outcomes of a five-year business analytics development window, including the development of an undergraduate core course, a graduate certificate, a minor, and an online master's program. Details on motivation, curriculum design, and course delivery, as well as tuition/value comparisons, are discussed in the paper.

While the majority of the extant literature focuses on reporting business analytics curriculum design outcomes and results, Clayton and Clopton (2019) focus on the earlier stages of designing a business analytics certificate program. They emphasize design thinking and put significant effort identifying key design goals. The result was the creation of a four-course program offered to undergraduate business majors. This paper is particularly noteworthy as it also addresses major barriers to the adoption of business analytics curricula at universities and colleges in general, with difficulty recruiting qualified instructors to deliver content reported as the biggest barrier to overcome.

2.2.2 Business Analytics Courses Targeted to Different Audiences. The business analytics education literature is quite diverse and addresses course offerings developed for a variety of different audiences—both general and domain-specific.

Much work focuses on introducing general business analytics concepts and skills (Rodammer et al., 2015; Yazici, 2020; Zhang et al., 2020) to serve a broad audience of learners from a variety of different business backgrounds working together. For example, Zhang et al. (2020) showcase the design and implementation of an elective business analytics class for all business majors. This paper includes details on potential course topics for a general audience, including timelines, sample assignments, and proposed lab work. In another study, Yazici (2020) demonstrates the effectiveness of project- and problem-based methods to teach an introductory business analytics class suitable for all undergraduate business students. A four-phase learning methodology is proposed with lab projects created by mapping out the four different phases. Additionally, Rodammer et al. (2015) reconceptualize two existing core business courses into business analytics offerings. They redesign an entry-level freshman class, titled *Concepts of Computing*, into a new *Problem Solving with Data Analytics* course. They also redesign a core business information technology course targeting sophomores and juniors into a higher value *Business Analytics and Information Systems* course. For each newly designed course, learning objectives and major topics of interest are presented.

Conversely, a different body of extant work takes a domain-specific direction where offerings are designed and developed to deliver functionally-relevant business analytics content to a targeted subset of learners (Dzuranin et al., 2018; Liu & Burns, 2018; Liu & Levin, 2018; Tremblay et al., 2016). For example, Liu and Levin (2018) investigate how to systematically teach analytics in the marketing curriculum and propose a progressive approach where students gain more exposure over time. Here, different analytics components are tied to each marketing course offering in the major, with a new upper division course offered where the individual components come together in a culminating capstone experience. Additionally, Liu and Burns (2018) analyze a rich data set of survey responses from business executives using LinkedIn, 400 business analytics-related job postings, over one million analytics-related tweets from Twitter, and 13 marketing business analytics course syllabi. Here, they use these rich data sources as the basis for determining marketing business analytics course design guidelines. Based on their analyses, they compiled a list of key business analytics topics that are appropriate for marketing course offerings.

Beyond marketing, other domains such as healthcare and accounting have shown extremely strong interest in the inclusion of specific business analytics content. For example, Tremblay et al. (2016) describe efforts at Florida International University (FIU) to develop a master-level health informatics and analytics program. The authors discuss the issues, challenges, and lessons learned in the development of the program, as well as offer details on students' success in completing the program. Additionally, Dzuranin et al. (2018) complete a broad exploratory survey of accounting faculty regarding which data analytic skills and tools should be taught, including where, how, and when students should be exposed to this material in their accounting degree progress. The authors find that combining the "focused" and "integrated" methodologies together by incorporating stand-alone accounting business analytics courses with embedded analytics material in existing "traditional" accounting courses as the most welcomed approach to incorporate business analytics content into the accounting curriculum.

2.2.3 Business Analytics Courses by Level of Student Sophistication. Business analytics course design decisions are largely reliant upon the sophistication of the student audience targeted. Sophistication is a critical consideration for course design given the highly technical nature of certain business analytics content and the wide diversity among students, from a general/non-technical audience (Dean, 2020; Yazici, 2020) to a specialized/highly technical audience (Asamoah et al., 2017; Eckroth, 2018; Klašnja-Milićević et al., 2019).

On the general or non-technical end of the spectrum, the extant literature provides insights on how to deliver introductory-level business analytics content to a general audience of students from different backgrounds (Dean, 2020; Yazici, 2020). Several studies have highlighted the importance of designing introductory-level business analytics courses that are appropriate for all business majors and non-business majors from across a variety of disciplines. For example, Yazici (2020) discusses the development of a fundamental business analytics course that is required for accounting, finance, economics, and IS majors, and an elective option for other majors. Yazici emphasizes the importance of problem- and project-based learning and pointed out that, compared to traditional lecture and exam-based learning, problem- and project-based learning approaches are more effective in developing student analytical and critical thinking skills. In another study, Dean (2020), while presenting a general business analytics course for all business majors, proposes a learning assistant model built around an active learning philosophy. The novel aspect of the model is shifting the classroom from a traditional lecture-based approach to an active learning environment using student peers to facilitate small group discussions. Students, on average, who complete the course with the learning assistant model in place earn higher marks than students who complete the traditional, lecture-based course instead.

On the specialized/technical end of the spectrum, the existing literature provides insights on how to deliver advanced business analytics classes requiring an intensive programming background (Eckroth, 2018), as well as how to create courses that are specifically designed for senior-level and/or graduate-level students seeking mastery of advanced algorithms and business analytics tools (Asamoah et al., 2017; Klašnja-Milićević et al., 2019).

Specifically, Eckroth (2018) designs and delivers a technologically-intense upper-level business analytics course targeted to computer science majors. Eckroth provides detailed course learning objectives and course schedule outlines, as well as specifics on the five technical, hands-on lab projects that are embedded throughout the course. Eckroth's course is likely too technical for a general audience due to the required use of different programming languages, including Java, C++, and Python. Additionally, this course requires students to apply several highly technical analytic tools. In another study, Asamoah et al. (2017) detail the design of an elective business analytics course for senior and graduate-level students with strong technical and quantitative backgrounds. The course is attractive for IS majors, as well as computer science and engineering students, with 83% of students studying at the graduate level. Helpful details on course objectives, course modules, sample labs, and assessments are provided in their paper.

Additionally, Klašnja-Milićević et al. (2019) present details regarding the design and implementation of a graduate-level class focusing on business intelligence in the Mathematics and Informatics domain. They include learning objectives and course topics, and describe the overall course structure, including lectures, presentations, demonstrations, and hands-on exercises.

2.2.4 Business Analytics Courses Under Unique Situational Circumstances. In addition to the studies regarding the design and implementation of business analytics-related classes based on different domains, target audiences, and level of student sophistication, there are also a subset of studies focusing on how to best tailor business analytics coursework to certain situations or unique environmental conditions, including course delivery during the COVID-19 pandemic (Sharef & Akbar, 2021; Williams & Elmore, 2021).

Sharef and Akbar (2021) present a case study on the instructional design of a business analytics class during the COVID-19 pandemic using a Massive Open Online Course (MOOC) platform. They discuss the learning analytics dashboard provided by the MOOC platform, including students' usage of each online support feature. Furthermore, Williams and Elmore (2021) discuss challenges of teaching business analytics classes online during the COVID-19 pandemic and suggest best practices. Here, they address two business analytics offerings at different levels, including a general education course required for all business majors and an upper-division elective course with advanced techniques targeted at a technical audience. Specific challenges, including student engagement and problems in learning the business analytics software, are identified with potential problem solutions and recommendations for implementation offered. The authors summarize several takeaways and insights from their study, including the importance of building class community, a preference toward unpacking asynchronous material into micro-sized units, and the necessity of incorporating enhanced flexibility around each learning outcome.

Based on the above discussions, Table 1 summarizes several key studies that focus on business analytics course design and development. The level of scope (course level vs. curriculum level), target audience (general business vs. specific functional area), and degree of sophistication (general/non-technical vs. technically-intensive education) of these studies are highlighted. While many of these studies use the term "business analytics," others prefer the terms "business intelligence" or "data analytics." Each of these studies generally shares the same philosophy of leveraging analytical algorithms and techniques as a means to make sense of business data and as a key mechanism to drive better strategic decision making.

Our review reveals a rich body of existing literature on business analytics education, as well as a potential gap to be addressed. Unfortunately, most business analytics course development efforts assume that students seeking general, introductory-level concepts and skills must be separated from those students who seek sophisticated, programming-oriented education that introduce advanced techniques and algorithms. Course design work that brings these two disparate groups together could be of tremendous value to the business analytics education literature.

Consequently, this study aims to introduce a business analytics course design that is robust enough to prepare students for advanced business analytics training, without requiring computer programming prerequisites.

Additionally, most of the existing literature neglects to include a systematic assessment component. Thus, this study adds additional value by incorporating a longitudinal survey methodology to systematically evaluate the effectiveness of course development efforts.

3. DESIGN AND DEVELOPMENT OF THE BUSINESS ANALYTICS COURSE

3.1 Course Goals, Learning Tools, and Learning Objectives

This section details our course design, including learning objectives, learning modules, and course components. The business analytics course presented in the current study is a senior-level, undergraduate business analytics course offered to business students at a southwestern university in the United States. This course is required for IS and marketing majors and is an elective offering for the remaining majors in the business school (i.e., accounting, economics, finance, and general management).

The overarching goals of this course are (1) to provide students an opportunity to learn key concepts and hands-on business analytics skills so that they are better prepared to perform BA-related tasks for real-world application, and (2) to offer students an in-demand career path by preparing them for careers in business analytics post-graduation.

As highlighted previously, most business analytics courses focus on either general introductory-level business analytics content with no expectations of prior programming experience or on specialized domain-specific content with expectations that students have mastery of basic business analytics tools with technical programming skills to perform high-level analyses.

Study	Level of Scopes	Target Audience	Student Sophistication
(Pomykalski, 2021)	Course level	IS focus	General education
(Sharef & Akbar, 2021)	Course level	Computer science focus	Technical intensive
(Williams & Elmore, 2021)	Course level	General business audience	Two courses, with one being for general education and the other technically intensive
(Zadeh et al., 2021)	Course level (sample business analytics exercise)	General business audience	General education
(Dean, 2020)	Course level	General business audience	General education
(Yap, 2020)	Course level (specifically on dashboard design)	General business audience	General education
(Yazici, 2020)	Course level	General business audience	General education
(Zhang et al., 2020)	Course level (one design applied at two universities at US and Canada)	General business audience	General education
(Clayton & Clopton, 2019)	Curriculum level (a 4-course business analytics certificate program)	General business audience	General education
(Klašnja-Milićević et al., 2019)	Course level	Mathematics and Informatics focus	Technically intensive (for graduate students)
(Dzuranin et al., 2018)	Course level	Accounting focus	General education
(Eckroth, 2018)	Course level	Computer science focus (for junior and senior computer science students)	Technically intensive (an upper-level class for computer science majors, programming intensive)
(Liu & Levin, 2018)	Curriculum level	Marketing focus	General education
(Olson, 2018)	Both course and curriculum levels (an undergraduate core course, a graduate certificate, a minor, and an online master's program on BA)	General business audience	General education
(Asamoah et al., 2017)	Course level	General business (but for students with strong technical backgrounds)	Technically intensive (for seniors and graduate students)
(Tremblay et al., 2016)	Curriculum level	Healthcare focus	General education
(Molluzzo & Lawler, 2015)	Curriculum level (IS curriculum with a business analytics concentration)	IS focus	General education
(Rodammer et al., 2015)	Course level	General business audience	General education

Table 1. Examples of Business Analytics Education Related Literature

The current study conceptualizes a business analytics course that aims to bridge those two groups of development effort. First, we prioritize delivering a course that introduces business analytics skills, techniques, and algorithms so that students are best prepared to enter the business analytics job market as a career path. Second, our course offering targets both technical and non-technical learners instead of focusing on one distinct group over the other. We chose not to emphasize a requirement for students to have existing technical skills and prior programming experience, so that students from different backgrounds can take advantage of this learning opportunity. To do this, a data science platform called RapidMiner (https://rapidminer.com) was incorporated during course design, which offers template-based frameworks that are easy to understand. RapidMiner is a very powerful business analytics instrument that incorporates all phases of business analytics processing—data cleaning and preparation, data mining and modeling, and data deployment and representation. RapidMiner is advanced enough for students to practice specific business analytic techniques and algorithms but does not require users to write their own code. Figure 1 offers an example of using the design interface in RapidMiner to create a process for association rule analysis. This is a powerful tool as it provides a drag-and-drop mechanism to add operators one by one into the process, with each operator performing a particular data preparation or analysis-related activity. This figure also shows the graphic user interface that easily allows users to set up the various parameters for each operator.

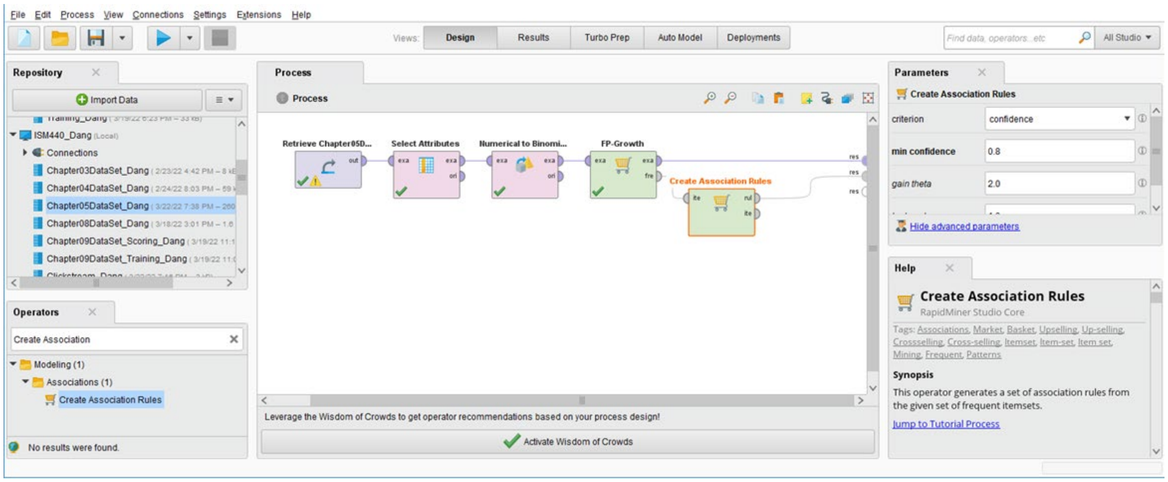

Figure 1. Example of RapidMiner Interface

As discussed in Zadeh et al. (2021), the pedagogical framework for big data and social media analytics follow a series of important modules, including data collection, data storage, data preprocessing, data integration, data analysis, and data visualization. The data collection, storage and preprocessing modules are mainly about cleaning and organizing the raw data, while data integration and analytic techniques are focused on making sense of data. The final module, data visualization, is driven by the proper presentation of data. Each of these modules are addressed in our course, with the greatest effort placed on data analysis.

The specific learning objectives (LO1-LO7) for our business analytics course are:

- LO1: Demonstrate the role of data in managerial decision making.
- LO2: Understand the distinctions between a transactional database and a data warehouse.
- LO3: Develop an understanding of supervised learning and unsupervised learning.
- LO4: Demonstrate the fundamentals of data mining techniques.
- LO5: Demonstrate the use of data analysis techniques to make better business decisions.
- LO6: Demonstrate the ability to construct analytical models based on business data.
- LO7: Develop visual analytics models.

3.2 Course Structure and Components

Table 2 lists the major topics covered in the class, as well as the order of introduction to students, which is designed to be delivered over a 16-week semester.

Guided by experiential learning theory (see Morris, 2020 for a review of literature) and active learning theory (see Prince, 2004 for a review), the course was designed with both interactive lectures and a heavy use of hands-on lab projects. For each course topic, an interactive lecture where the statistical and mathematical foundation of the related technique and algorithm (as well as the conditions to use and apply the technique/algorithm) are included. Demonstrations are an integral part of each lecture, so students gain a general understanding of how to best apply the technique or algorithm to solve a real-world problem. To further reinforce the notion of active learning, students are asked to follow the demonstration steps on their own. Then, a hands-on lab project is assigned so students can practice building their own experiences and apply the latest techniques learned to a specific problem. This "hands-on" approach directly applies active learning theory and offers students multiple opportunities to build their own "experience" via personal discovery.

Order	Major Topics
1	Introduction to Business Analytics and RapidMiner
2	Data Exploration and Visualization
3	Supervised Learning: Linear Regression
4	Supervised Learning: Logistic Regression
5	Unsupervised Learning: Association Analysis
6	Supervised Learning: K-Nearest Neighbor
7	Supervised Learning: Decision Trees
8	Supervised Learning: Artificial Neural Networks
9	Unsupervised Learning: Clustering

Table 2. Major Topics and the Introduction Order

In addition to introductory lab projects, two more advanced types of lab projects (i.e., problem-solving lab projects and lab project exams) are also included for students to gain higher-level mastery of the various techniques and algorithms they are learning in the class. The major difference between the three types of lab projects involves the amount of instruction provided to students. By offering multiple opportunities to practice, with lesser direct guidance as the level of sophistication and understanding increases, students will be forced to increasingly rely on their own critical thinking skills to reach deeper mastery.

Here is a breakdown of the three categories of lab work:

- *Regular lab projects* provide the most detailed instructions for students to follow. The main purpose of each project is for students to practice applying a particular technique/algorithm, gain experience and comfort level, and, perhaps most importantly, to reflect and learn from their initial experiences.

- *Problem-solving lab projects* offer fewer instructions than regular lab projects. These projects are designed to promote critical thinking and include discussion questions for students to report on while they address a contemporary problem. The purpose of problem-based lab work is to reinforce students' experience using and applying the focal techniques/algorithms.
- *Lab project exams* contain the least number of instructions and are used as a formal means to assess student performance and understanding. For each lab exam, students will typically be asked to complete an entire business analytics process on their own (e.g., data importing, pre-processing, modeling, representation, and visualization).

Figure 2 details the main course design components focusing on active and experiential learning. Details on the course content are provided in Appendix A.

4. ASSESSMENT OF THE BUSINESS ANALYTICS COURSE

4.1 Assessing Improvement in Student Learning

This section addresses the assessment of the course design, including quantitative analyses using pre- and post-course surveys to determine student understanding of business analytic techniques, attitudes toward business analytics, student engagement, and interest toward learning.

As discussed previously, the existing literature on business analytics course development reveals limited effort made regarding assessment of learning. Several studies utilize end-of-semester course evaluation results as an assessment mechanism, while others use a list of qualitative questions at semester end to seek students' feedback. Unfortunately, many others did not include an assessment component at all.

One exceptionally strong study done by Jewer and Evermann (2015) proposed a learning outcome assessment framework, which guided our thinking on how to best evaluate the effectiveness of our course design. The framework includes four dimensions of assessment: student understanding, student engagement, student learning, and student learning interest.

According to this framework, student understanding is measured pre- and post-exposure to certain learning materials to determine whether understanding has improved. For our study, an eight-item measure for this dimension was developed, with one item addressing overall understanding of analytics and the remaining seven items specifically targeted to the course learning objectives (i.e., LO1-LO7). These items are each measured twice, once at the beginning of the semester and again toward the end of the semester.

For each of the other three dimensions (i.e., student engagement, learning, and learning interest), the framework suggests measurement after students' exposure to the learning materials. For our study, measurement items from Jewer and Evermann (2015) were adopted, with modifications to fit the content and purpose of our study. These items are measured once toward the end of the semester.

In addition to the Jewer and Evermann (2015) framework, students' attitudes toward business analytics both before and after course completion (or at the beginning and conclusion of the semester) are also measured. This purpose of assessing attitudes over time is so we can determine whether the business analytics class helped to shape a more positive view of the business analytics field. To measure student attitude, items from Venkatesh et al. (2003) were adopted with minor changes in wording to match the context of our study.

In the education literature, two common measures on learning success are learning satisfaction and intention to learn (Chiu & Tsai, 2014; Lin, 2012; Mohammadi, 2015; Sun et al., 2008). For our study, learning satisfaction and learning intention are measured at the end of semester to not only assess whether students are satisfied with the business analytics class, but also, to help determine whether they intend to continue learning more about business analytics after course completion. Items for learning satisfaction were adopted from Mohammadi (2015), and items for intention to learn more in the future were adapted from Venkatesh et al. (2003), with minor wording changes to fit the study context.

The detailed items for each of the measurement dimensions are provided in Appendix B. All items were measured using a 7-point Likert scale, with "1" as strongly disagree and "7" as strongly agree. The scale mid-point is "4."

As mentioned above, certain items were measured twice, at both the beginning and the end of the semester, while other items were measured once at the conclusion of the semester. The time 1 survey dimensions were administered to students in the second week of the semester; the time 2 survey instrument was administered at about two weeks before the end of the semester. Students' participation in this study was voluntary. As an incentive, extra credit amounting to a very small percentage of the total class points possible was offered to those who completed each survey.

The study was conducted over two semesters (Fall 2021 and Spring 2022) using a total of four sections of this course, all of which were taught by the same instructor. Overall, survey invitations were sent to 167 students. For the initial survey (i.e., time 1), 104 students participated (generating a response rate of 62.3%). For the post-course survey (i.e., time 2), 121 students participated (generating a response rate of 72.5%). There was a total of 86 students who completed both surveys (Note that names were collected for granting extra credits, but their participation were voluntary). Among the final respondents, there were 38 male students and 48 female students. Their average age was 21.19, with the average number of years in college at 3.65. The demographics of final respondents were generally representative of the larger group, which tended to be of traditional college age and slightly more female. Pairwise t-tests were conducted using the data for the measures of student understanding and attitude from the final 86 student respondents. Table 3 summarizes the descriptive statistics and the t-test results.

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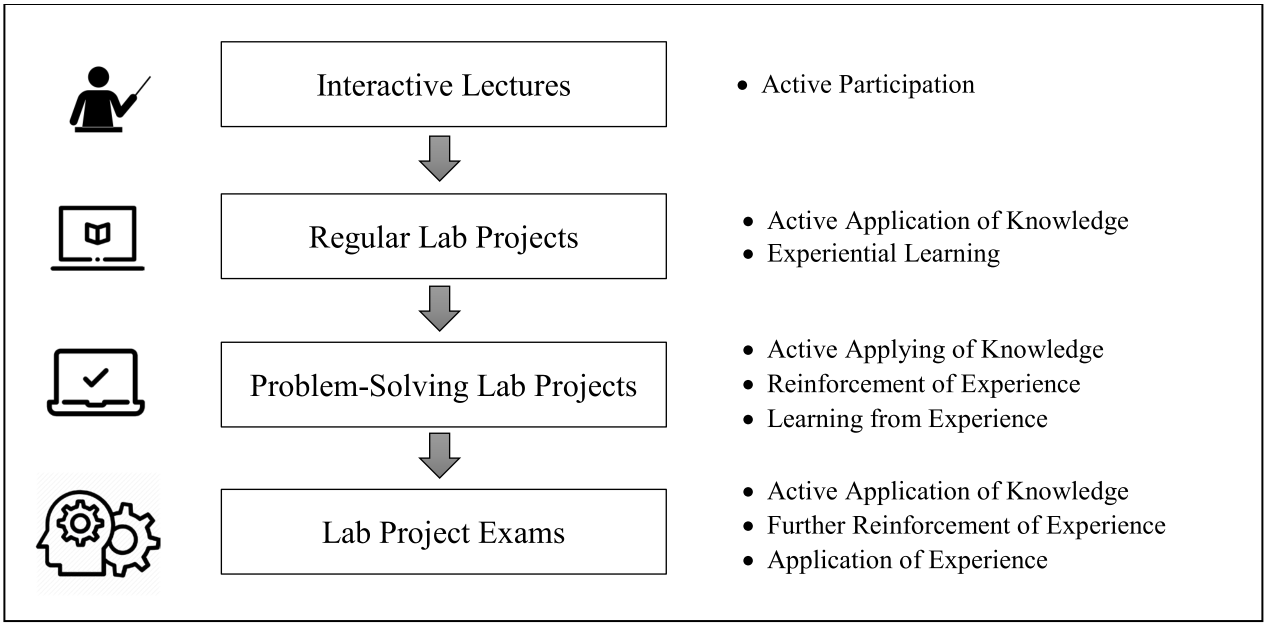

Figure 2. Main Course Design Components

Dimension	Pre-Course Survey		Post-Course Survey		p-values	t-stats
	Mean	Std. Dev.	Mean	Std. Dev.		
Understanding - Overall	3.965	1.367	5.477	1.215	<0.0001	9.869
Understanding - LO1	4.221	1.498	5.512	1.186	<0.0001	6.670
Understanding - LO2	3.430	1.627	5.221	1.418	<0.0001	9.313
Understanding - LO3	4.744	1.603	5.523	1.155	<0.0001	4.004
Understanding - LO4	3.140	1.550	5.628	1.074	<0.0001	13.259
Understanding - LO5	3.733	1.641	5.686	1.066	<0.0001	10.206
Understanding - LO6	3.407	1.690	5.721	1.048	<0.0001	11.647
Understanding - LO7	3.360	1.735	5.837	1.105	<0.0001	12.490
Attitude toward BA	5.016	1.318	5.298	1.286	0.020	2.085

Table 3. Descriptive Statistics and T-Test Results for Improvements in Engagement and Attitudes Toward Business Analytics

At the beginning of the business analytics class, students on average, perceived their overall understanding of business analytics as "neutral" (or around 4, which is the scale mid-point). However, after completing the course, perceptions of overall understanding of business analytics significantly improved with mean score of 5.48 out of 7 ($p < 0.0001$).

The average ratings on each of the learning objectives of the class in the pre-course survey were also close to the scale mid-point (with most being slightly lower than the mid-point). It is interesting to note that the average ratings among each of these dimensions improved significantly in the post-course survey, with mean values ranging from 5.22 to 5.84 out of 7 ($p < 0.0001$). These results, taken together, indicate significant improvement over time in students' understanding of business analytics concepts.

On average, students' attitudes toward business analytics were largely positive with a mean of 5.02 out of 7 before course exposure to any specific business analytics techniques or algorithms. This finding is not overly surprising and may be indicative of students' general understanding of the importance of business analytics techniques, which positively shapes their openness to the topics and a continued interest toward learning. After exposure to active and experiential learning activities throughout the semester, students report more positive attitudes toward business analytics (with a mean rating of 5.3 out of 7), a statistically significant increase in attitude over time 1 ($p = 0.020$).

4.2 Post-Course Learning Assessment

To further assess course design, we follow the work of Jewer and Evermann (2015) to address the remaining three learning outcome dimensions (i.e., student engagement, learning, and learning interest). Here, survey data were collected at the end of the semester (i.e., time 2), and comparisons were made against the scale mid-point. The same comparisons were also conducted for learning satisfaction and intentions to learn. We used the data collected from all 121 participants who completed the time 2 survey and conducted t-tests based on the ratings on these dimensions as compared to the scale mid-point (i.e., 4). Of the 121 time 2 respondents, 61 were male and 60 were female students. As a group, they were 21.49 years old on average, and were enrolled in college for an average of 3.67 years. Table 4 displays the descriptive statistics and the t-test results.

On average, after taking the business analytics class, students report positive attitudes on all measurement dimensions, including student engagement, student learning, learning interest, satisfaction, and intention to learn. Among them, learning satisfaction had the highest overall rating (5.813 out of 7), followed by student learning (5.713 out of 7) and student engagement (5.245 out of 7). T-test results, comparing to the scale mid-point values, show that on average students have significantly positive views for each of these dimensions, suggesting once again a highly effective course design.

Dimension	Mean	Std. Dev.	p-values	t-stats
Student Engagement	5.245	1.523	< 0.0001	8.993
Student Learning	5.713	1.041	< 0.0001	18.105
Learning Interest	4.879	1.637	< 0.0001	5.905
Learning Satisfaction	5.813	1.181	< 0.0001	16.887
Intention to Learn	4.853	1.615	< 0.0001	5.812

Table 4. Descriptive Statistics and T-test Results on Student Engagement, Student Learning, Learning Interest, Learning Satisfaction, and Intention to Learn Business Analytics (Comparisons Made to Scale Midpoint)

5. DISCUSSION

Our design and assessment of a senior-level, undergraduate business analytics course contributes to the existing business analytics education literature in three fundamental ways. First, the current course is designed to expose students from different backgrounds to an intermediate/advanced level of business analytics. We aim to attract students majoring in IS and other computing-related disciplines, as well as students from a variety of different backgrounds who can benefit from business analytics experience, including students without prior programming backgrounds. To make it possible for these two student groups to work together, we carefully researched and adopted a business analytics platform called RapidMiner. This software has a powerful user interface and a broad student body that understands it, and is populated with many template frameworks, so programming backgrounds are not required. Students can be subjected to business analytics skills and apply knowledge learned without needing to complete a long list of pre-requisite or highly technical courses. Consequently, the business analytics course is robust enough to serve as a required course offering for both IS majors who are typically "tech savvy" and Marketing majors who generally have little to no computer programming experience. In the meantime, this course can also serve as an elective course offering for other business majors as well. The in-depth nature of the course topics also makes this course appropriate for computer science, informatics, and engineering majors. We hope our course design can serve as an example to educators interested in delivering business analytics to students from various backgrounds and differing levels of technology efficacy.

Second, following experiential learning and active learning theories, we designed a course structure with heavy emphasis on lab projects. In particular, three types of active learning-based lab projects were developed for students to gain, reinforce, and apply experiences. After a particular course topic with techniques and algorithms is introduced via an interactive discussion format, a guided lab project with step-by-step instructions helps students build initial comfort and experience on using those new techniques via the "learning by doing" mechanism. Next, problem-based lab projects with fewer instructions are provided to students so they can reinforce and apply what they have already learned from their experiences with the regular lab projects. This extra exposure gives them another chance to build experiences and solidify their knowledge set. Then, lab project exams with even fewer instructions allow students another opportunity to reinforce experiences and apply what they have learned to higher level business analytics problems. Students should gain more and more comfort with business analytics content after successfully completing this series of increasingly sophisticated lab projects.

Third, this study is unique in that it includes a systematic assessment of our business analytics course design. Based upon our review of the extant literature, most research studies focusing on the design and development of business analytics courses and curricula have a relatively weak assessment component (Eckroth, 2018; Klašnja-Milićević et al., 2019; Liu & Burns, 2018; Molluzzo & Lawler, 2015; Olson, 2018; Zhang et al., 2020). Few studies have systematically conducted quantitative analysis based on specific theoretical constructs to demonstrate design effectiveness. We hope the assessment component of this study can serve as an example for future research. Pre- and post-course comparisons indicated that students gained significant improvements in their understanding and overall attitudes toward the business analytics subject. Additionally, results indicate that students had formed significantly positive assessments of engagement, learning, learning interest, learning satisfaction, and intention to learn after completing each of the modules in the business analytics class. Overall, these results indicate a high level of effectiveness in business analytics course design.

Our hope is that this course design approach will engender a virtuous cycle where students gain exposure to content and, then via a pattern of increasingly sophisticated active learning experiences will realize positive psychological outcomes. For example, as students gain success with initial lab work, their feelings of efficacy about being able to complete advanced lab work should increase as well. As self-efficacy increases, future interest in business analytics content should increase as well—perhaps to the point where students seek business analytics jobs post-graduation.

We have seen the landscape around business analytics shift quite dramatically over time. In fact, our university is in the early development of an undergraduate multidisciplinary business analytics degree program. The salient success of the current business analytics course offering has generated considerable enthusiasm and has shown that technical and non-technical students can successfully build meaningful learning experiences together. As we move forward, we conceptualize the need for three categories of business analytics courses: (1) business analytics offerings that focus on data pre-processing and storage via the use of data warehousing, (2) business analytics offerings that are similar to the course introduced in this study and focus on advanced data analysis and modeling, and (3) business analytics offerings that are domain-specific—such as marketing or accounting—and address real-world decision making.

This current study also has several limitations that future research may consider as areas for improvement. First, we only focused on one business analytics course design that aimed to teach students business analytics from primarily a data mining perspective. Since business analytics is a large field with different types of techniques and methods that could be utilized to make sense of business data, future research could consider other perspectives for developing business analytics courses. In addition, a comprehensive study with a systematic assessment on the design of a business analytics program with the integration of multiple courses focusing on different perspectives could be very beneficial to current literature. Second, the main focus of this current study is on the design of a business analytics course, and the assessment variables used in the study are to evaluate the effectiveness of the course design. The use of T-tests could be a limitation of the current study, and future research may consider using more advanced statistical methods to investigate student learning in business analytics courses. For example, future research may take a different perspective to investigate how different variables could possibly influence student learning outcomes. A research model could be developed and tested accordingly. Also, the target audience of our course is senior undergraduate students. We hope our class design ideas could bring some insights to educators who are planning to create business analytics courses for the same or similar student bodies. But more investigation needs to be done to see whether the overall course design idea could possibly fit other groups of students. Based on the characteristics of the serving student bodies, other important teaching mechanisms may be needed. Furthermore, given the persistent challenge of a shortage of competent faculty in teaching business analytics, coupled with the increasing demand for business analytics classes among students, future research should delve into effective strategies for designing collaborative business analytics courses.

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APPENDICES

Appendix A. Detailed Information on Course Content

Here is a breakdown of how we organized and presented this course to students.

Each week, when a particular topic is introduced to students, a PowerPoint lecture on that topic was initially presented to students in the hopes that they will gain a general understanding of the most important concepts from a data mining perspective. Next, a thorough demonstration on how to use the RapidMiner system to apply the data mining method is presented in the second part of the initial lecture/discussion. All students are strongly encouraged to follow the demonstration with the course instructor and to practice the sample problem using RapidMiner by themselves during the remaining class time. This practice time not only helped students to reinforce what they had learned from the lecture, but also helped to drive students' comfort using the RapidMiner software to complete various data analytics tasks. In our assessment, this step is particularly helpful for the non-technical students who likely need extra practice to build confidence and efficacy.

After the lecture/discussion/practice, students are asked to complete a quiz which is designed to assess their understanding of the technical content learned for a given topic. In addition, a lab project is given to students, asking them to use the new algorithm presented that week to solve a new problem. Students inevitably need to understand the meaning of the dataset, they need to be able to successfully apply the data mining methodology presented, and, perhaps most importantly, they need to be able to generate and interpret the analysis results. It is our experience that students often must be pushed to reach salient conclusions from their analyses, as this step is critical to convert data into usable knowledge.

To further help improve students' learning success and drive mastery of the RapidMiner software, problem-based lab projects as well as lab project exams are also used to facilitate learning and drive assessment. At this point, students not only need to know how to implement a process and apply a particular data mining methodology on a real-world dataset, they also need to employ critical thinking activities from raw dataset review to final analysis and reporting of results.

Finally, students are asked to use their results to address several decision-based questions. Deliverables that exceed expectations are those that apply what was learned to a specific organizational problem, and use results as the basis for specific action planning.

Appendix B. Items for Assessment Measures

Understanding

[For pre-course survey]: At the current stage (i.e., beginning of the semester),
[For post-course survey]: At this stage of the class (i.e., almost the end of the semester),

- I have a good understanding of business analytics (both the conceptual and technical aspects).
- I am able to explain the role of data in managerial decision making.
- I am able to explain the distinctions between a transactional database and a data warehouse.
- I understand supervised learning and unsupervised learning.
- I am able to demonstrate the fundamentals of data mining techniques.
- I am able to use data analysis techniques to make better business decisions.
- I am able to construct analytical models based on business data.
- I am able to develop visual analytics models.

Attitude

- Learning business analytics is important.
- Learning business analytics is fun.
- I like learning business analytics.

(Student) Engagement

- This class has held my attention.
- This class has excited my curiosity.
- This class is engaging.

(Student) Learning

- This class has increased my understanding of concepts related to business analytics.
- This class has increased my understanding of techniques related to business analytics.
- This class has helped me to learn concepts related to business analytics.
- This class has helped me to learn techniques related to business analytics.

Learning Interest

- This class has increased my interest in learning business analytics.
- This class has increased my interest in doing additional reading on business analytics related topics.
- This class has increased my interest in doing more exploration on business analytics related topics and issues.

Learning Satisfaction

- I am pleased with the business analytics class.
- I am satisfied with the business analytics class.
- The business analytics class satisfies my learning needs.

Intention to Learn

- After taking this class, I would like to do more exploration and further learning on business analytics.
- After taking this class, I intend to learn more about business analytics.
- After taking this class, I am willing to learn more about business analytics.
- After taking this class, when there is an opportunity, I would like to continue my learning on business analytics.

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