Development of an Introductory MBA Course in Business Analytics Using Data-Driven Decision-Making (DDDM) Model

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Business Analytics has become an important field of study in the MBA curriculum. Over the last decade, many MBA programs have added Business Analytics (BA) courses into their curriculum. Unlike most other disciplinary area courses that are somewhat similar across MBA programs, BA courses tend to vary significantly in content and structure depending on the faculty who teaches it. Thus, very little systematic guidance is available to faculty who are considering developing and teaching a BA course in the MBA program. One important pedagogical concern is making MBA students understand the importance of Business Analytics in making data driven decisions. This paper presents a conceptual model of the data-driven decision-making process that was the foundational guide for the methodical development of a BA course and its implementation. Some implications of this model for development of BA courses for MBA programs are also presented.

Keywords: decision-making, business analytics, MBA, course development

INTRODUCTION

One could argue that analytics owes its origin to the Hindu-Arabic numeric system (that included zero – ninth century) for data and the development of scientific method and probabilities (17th through 19th century) for modeling as presented by Buchanan and O'Connell (2006). The first well documented use of data (numeric, temporal, and geographic) for decision making is the study of the cholera epidemic by John Snow in 1854 (Tufte, 1997). With the availability of computing to add to data and modeling, business analytics has become a strategic tool for decision making and competitive advantage in many organizations since the concept was introduced in the 2000's. Davenport & Harris (2007) defined analytics as "the extensive use of data, statistical and quantitative analysis, explanatory, and predictive models, and fact-based management to drive decisions and actions." Analytics helps to discover meaningful patterns, new and novel information, insights, and knowledge, in data that can help managers make better decisions. Business analytics (BA) has been defined to be "a special application/subset of analytics that leverage its tools, techniques, and principles to develop solutions to ever so complex business problems" (Delen and Ram, 2018, pg. 2). According to Warner (2013), Business Analytics is a critical area of study in the MBA program. Students who understand and can consume analytics are valuable in the marketplace because one of the many factors that separate failures from success is their ability to effectively use analytics to make better decisions (Warner, 2013).

Davenport and Patil (2012) identified that a huge shortage of analytically skilled employees, such as data scientists, is a serious challenge for organizations moving into data driven decision making economy. In a report for McKinsey, Manyika et al. (2011) projected that United States alone could face shortage of 140,000 to 190,000 people with deep analytical skills and 1.5 million managers and analysts well-versed in the use of analytics to make effective decisions by 2018. According to the U.S. Bureau of Labor Statistics, the demand for well-trained business and management analysts is projected to increase by 14% between 2020 and 2030, compared to 8% average growth rate for all occupations.

Since BA has become so important in organizations, universities took up the challenge of developing BA knowledge and skills among their graduates by introducing degree programs in BA and courses in BA in their graduate programs and this trend has exploded over the last decade. The number of universities offering graduate programs in BA and courses related to BA in their MBA programs have increased tremendously. According to Rappa (2014), there were nearly 250 programs that were offering advanced degrees in analytics in May 2022 producing 8,000 – 10,000 analytics graduates per year.

Initially, many business schools started converting their statistics, business intelligence, and management science courses into BA courses in their MBA programs. Faculty teaching these courses were assigned to develop and teach the newly introduced BA courses. Because of the lack of clear definition of BA at that time, the BA courses were heavily dependent on the background of the faculty who were assigned to teach these courses (Gorman & Klimberg, 2014). In the beginning, faculty assigned to teach BA courses could not depend on textbooks related to BA since there were none. Some faculty used customized books by putting together articles and cases from journals, and chapters from statistics, business intelligence, and management science books. Since then, publishers have started publishing books on BA authored by some of the faculty who were teaching the BA courses. This led to a wide variety of content in BA courses depending on the background of the faculty who were developing and teaching these courses. Some of the courses had statistics orientation whereas other courses had management science, decision sciences, Management Information Systems (MIS) and business intelligence orientation depending on the courses faculty developers were previously teaching.

Thus, the content of these BA courses was not consistent and were not based on any framework or model. New textbooks that were developed by the faculty who were teaching BA courses also had different orientation namely statistics, management science, MIS, and business intelligence. Some books cover descriptive, predictive, and prescriptive analytical models, whereas other books focus on descriptive and predictive analytical models only. Only few books evolved over time to cover topics based on the data mining models such as CRISP- DM (see Wirth and Hipp, 2000), SEMMA (see SAS, 2014), and KDD (see Brachman & Anand, 1996) models which grew as industry standards for developing data mining projects that define a set of sequential steps. Some schools decided to cover all types of analytics such as descriptive, predictive, and prescriptive analytics in one course and other schools decided to offer two courses with one course covering descriptive and predictive analytics and the next advanced BA course covering prescriptive and other advanced analytic topics such as big data and text analytics.

Due to the lack of systematic guidance in developing BA courses in MBA programs, a comprehensive process model could offer a solution. This model when used would lead to more consistency in course content and it would help in developing better targeted course materials. This would also make the process of course development more explicit. Since decision making is a journey, and not just a destination, the data-driven decision-making process should focus on the entire process of defining the right business problem, identifying, and collecting the right data, analyzing the data with right methods, and interpreting the results and implementing the right solution to solve the problem effectively. That is the approach taken in this paper.

This paper focuses on the development of a graduate BA course for the MBA program based on a data-driven decision-making model developed at a U.S. university by the authors. This approach to develop and teach the first BA course in the MBA program is entirely different compared to others, whose design was either driven by the background of the course developers or by the textbook they were using. The conceptual model of data driven decision making that shaped the design of an MBA course on Business Analytics will be discussed in detail. The process that was used in developing the course, the course content along with the assignments used, and the lessons learned from implementing the model will be presented in detail in the rest of the paper. Finally, implications of using the model for developing future courses in BA will be discussed.

REVIEW OF BUSINESS ANALYTICS CURRICULUM DESIGN LITERATURE

Over the past decade, universities have been responding to an increased demand for data analytics skills put forth by employers. As a result, institutions have been building analytics education and curricula, particularly in business-focused programs. During this time, the growth in analytics and related data science masters' programs has been impressive. Most of these are MS in Analytics (MSA) or MS in Business Analytics (MSBA) programs (Institute for Advanced Analytics, 2019). Due to this growth in analytics programs, academic interest in studying various aspects of analytics infusion in business education has also increased. Some prior studies have examined business analytics coursework in universities, particularly programs offered by business programs and classified them by matriculation level, subject area coverage, topic coverage, and pedagogies employed (Sircar, 2009; Phelps and Szabat, 2017). Others have viewed analytics programs through the lens of industry needs, workforce requirements, and employment opportunities (Radovilsky, Hegde, Acharya, and Uma, 2018; Mamonov, Misra, and Jain, 2015; Turel and Kapoor, 2016) and appraised the maturity of such programs relative to their potential to fulfill presumed industry needs. Detailed surveys of faculty, industry professionals, and students interested in analytics have formed the basis of successive surveys conducted at the BI Congress meetings. These surveys yielded insights about curriculum design, content coverage, and a need for interdisciplinary collaborative engagement that have been documented in the studies by Wixom et al (2011, 2014). In the remainder of this section, a handful of studies on BA curriculum research is discussed briefly.

In an early exploratory study (Sircar, 2009), business analytics was posited to lie at the intersection of management science, statistics, and information technology (IT) – all of which have been offered in traditional business curricula, both at the graduate and undergraduate levels. The study found that only 7 among top 50 business schools offered a course on business analytics at the undergraduate level, while 5 others offered related coursework in which business analytics topics were expected to be covered. Sircar (2009) acknowledged that coursework in decision sciences, statistics, and IT has traditionally always been integral to business curricula; yet the challenge was to consolidate important topics from these three areas in a coherent package that is either a standalone course in business analytics, or a BA minor or major.

Based on a survey of information systems faculty, industry professionals, and students, Wixom et al. (2011) recommended that universities must provide a broader range of analytics skills within analytics coursework and programs. The authors specifically recommended a broad/diverse range of topics for analytics coursework that includes business domain knowledge, research methods, statistics, data management, warehousing, and mining topics, quantitative analysis and operations research (OR), and systems analysis, design, and development.

Recognizing that no single department within a specific unit, for example, a business school could offer such a diverse array of topics, Wixom et al. (2011) pointed to the need to adopt a more collaborative approach of curriculum development that spans multiple departments or academic units. In a subsequent survey-based study, Wixom et al. (2014) found that an interdisciplinary approach cutting across traditional disciplinary silos involving faculty from different departments and schools was on the rise for developing, offering, and teaching analytics and related coursework. Wixom et al. (2014) further found that such an approach was increasingly commonplace in MBA programs in which the introductory analytics courses were being taught by marketing faculty. A notable contribution of this study was the nuanced recommendation that analytics curricular offerings must be distinguished based on the audience – undergraduate versus graduate, and MS versus MBA. For MBA coursework and executive education in analytics, greater emphasis on business applications of analytics at the enterprise level was recommended. Analytical skills that enable students to interpret business data and make informed decisions, along with management aspects of analytics projects were recommended to be essential for MBA analytics curricula. Viewed together, the Wixom et al. (2011, 2014) studies are instructive and provide early clues about development of a foundational curriculum model that can guide the design of a BA core course for an MBA program.

Consistent with Wixom et al. (2014), Gorman and Klimberg (2014) also noted that a greater focus on technical knowledge marks a point of distinction of MS programs in analytics compared to MBA programs, even though both seem to emphasize skills training that is applicable in the workplace. Like Wixom et al (2014), Gorman and Klimberg (2014) also delineated subject area coverage of statistics, OR, and MIS topics in MS courses in analytics and found that among surveyed programs, half of the content cover statistics topics, while the other half is largely evenly split between OR and MIS topics. Only 4 of the 32 institutions included in the Gorman and Klimberg (2014) survey offered MBA concentrations in analytics, while a vast majority offered MS in analytics degrees, limiting insights on design of MBA coursework on analytics.

Among contemporary prior research on analytics curricula, especially as it relates to the development of a conceptual model for data-driven decision-making, the recent work by Gupta, Goul, and Dinter (2015) is notable for providing the first analytics model curriculum. Based on extensive survey and review of prior literature in analytics, Gupta et al. (2015) provided a taxonomy of analytics and business intelligence topic coverage for undergraduate, MS, and MBA coursework, based on knowledge and cognitive process dimensions. Reiterating Wixom et al. (2014), Gupta et al. (2015) argued that MBA coverage of analytics should predominantly focus on strategic applications of analytical tools and technologies to solve business problems to derive competitive advantage, while MS coverage should emphasize technical dimensions such as how to build and deploy analytics applications using BI and BA tools. Gupta et al. (2015) prescribed inclusion of topics such as introductory concepts, IT frameworks and use cases for analytics, evolution of analytics in the organization, enterprise performance management, human resources for BI and analytics, business processes as they relate to analytics, enterprise application areas, predictive analytics and data mining, visualization, ethics, advanced topics, etc. in an MBA BA course.

Overall, with the exception of Gupta et al. (2015), detailed, well-researched BA curriculum development guidance especially for analytics coursework in MBA programs is virtually absent. Much of the prior work on analytics curriculum research has focused on MS in Analytics programs, consistent with the impressive growth in such programs. Yet, despite the increasing popularity of specialized MS programs, MBA programs offer a viable option for students interested in generalist business education to be exposed to analytics. As discussed earlier, in the absence of curriculum development guidance, analytics coursework design for MBA programs usually defaults to faculty with backgrounds in quantitatively oriented disciplines such as statistics, OR, industrial engineering, mathematics, and MIS, to name a few. Naturally, the course designer's academic, scholarly, and professional backgrounds are likely to bias course design. In addition, the absence of suitable teaching resources such as textbooks and case studies exacerbate the MBA analytics course designers' problems. Faculty end up designing courses based upon available textbooks that would otherwise be more suitable for MIS, OR, or business statistics coursework, or in some cases using textbooks that have been conveniently retitled to cater to the increasing demand of analytics coursework in business schools. This is neither desirable nor optimal, especially as the demand for skilled analysts continues to remain high in industry and is in fact predicted to grow.

Acknowledging that a single MBA course is hardly sufficient to produce a skilled analytics graduate, it nonetheless lays an important foundation for aspiring analytics professional. A curriculum design model that is built around the quartet of problem definition, evaluation of data requirements, application of analytical techniques, culminating in interpretation of results and problem solution, not only places a greater focus on business applications of analytics, as deemed appropriate in prior studies (Wixom et al, 2011, 2014; Gupta et al, 2014), it aligns analytics course design with problem-solving needs of contemporary businesses and industry at large. In addition, such a curriculum design model could guide development of appropriate teaching resources, optimal selection of course designer, and potentially pave the path for redesign of MBA coursework in MIS, quantitative methods, and strategy leading to an MBA that can produce well-rounded analytics professional.

In addition to reviewing prior BA curriculum design literature, a limited meta-analysis of syllabi of introductory Business Analytics (BA) courses in the MBA program from 16 different business schools/universities in the US was also conducted to better understand the design of existing introductory courses on business analytics in MBA programs. All 16 business schools are accredited by AACSB. All courses were 3 credit hour courses. All courses except for one course from a university in Texas had "Business Analytics" in the title of the course. Most of these courses did not have any pre-requisites except one that listed Business Statistics as pre- requisite for the BA course. The introductory BA course is required in the MBA programs in only 5 business schools whereas the other schools use them as electives. Only three courses were mentioned to be offered online.

Except for one business school, none of the BA courses were structured based on any conceptual model as per the syllabus. One school had structured their course on the CRISP- DM, six phase model. As far as the textbook is concerned, 8 schools required textbook(s), one school was found to use a course reader made available in their book store, one school provides articles available online, and two schools have optional recommended books.

A variety of analytics software tools are being used in the BA courses by the business schools in their MBA program. Some are less technical than others which requires programming skills. Six schools use Excel, followed by two schools each uses XL Miner and R. Other schools are using JMP, SAS, SAS Enterprise Miner, Weka, Power BI, Rapid Miner, Risk, and Tableau.

From the content point of view, most of the schools cover descriptive, predictive, and prescriptive analytics in their courses. Eight schools cover descriptive analytics (average – 17% of the semester with a range from 12% to 40%); all 16 schools cover predictive analytics in their BA courses (average – 48% of the semester with a range from 25% to 80%); and only 5 schools cover prescriptive analytics (average – 9% of the semester with a range from 6% to 33%). This indicates most BA courses cover descriptive and predictive analytics apart from some coverage on introduction to BA and Big Data.

This limited syllabus meta-analysis confirms that the BA course in many business schools do not follow any conceptual model and are either based on the textbooks they are using or the faculty's perception of what should be covered in the introductory BA course. This also points to a need for a model for structured course development for BA courses in MBA programs.

The next section outlines a conceptual model of data-driven decision-making process as a guide for developing an introductory MBA core course in analytics.

APPROACH TO BUSINESS ANALYTICS COURSE DEVELOPMENT

Rationale for Model

When faced with the task of developing a new course, it is common for faculty to search for existing courses elsewhere or conceptual models to guide them. This is no different with a business analytics (BA) course. One of the authors was tasked with development of a new introductory BA course for the MBA program early in 2018. This section details the process used for development and implementation of the course.

From the literature review, as presented in the previous section of this paper, it is clear that a single, commonly accepted, comprehensive model to guide development of BA courses does not exist. The development of our model is an attempt to fill this gap.

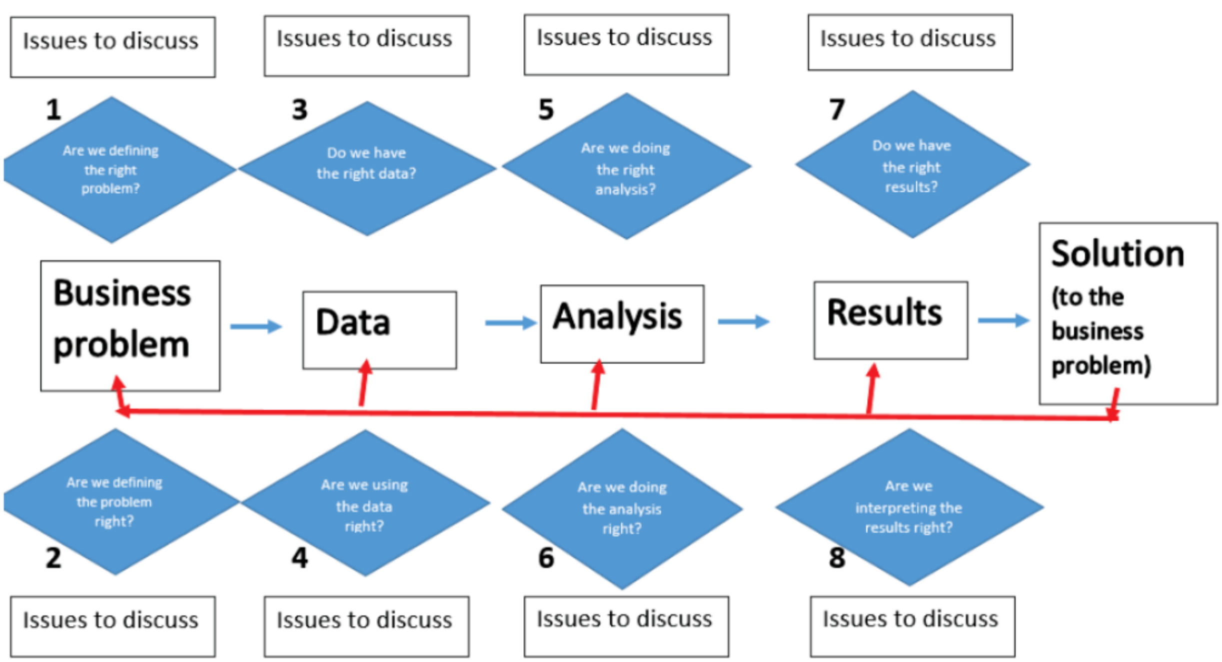
Data-Driven Decision-Making Process Model: Development

According to Haller & Satell (2020), International Data Corporation, the global market intelligence firm, projects spending on data and analytics to reach $274.3 billion by 2022. However, much of that money is not being spent wisely. Many of the big data projects fail. To get useful answers from data, we need to learn how to ask thoughtful questions – how the data was sourced, what models were used to analyze it, and what was left out (Haller & Satell, 2022). Jeyaraj (2019) developed a pedagogical framework that enables students to experience end-to-end learning on the related activities of data acquisition, preparation, analysis, visualization, and interpretation for decision making. Students provided indirect evidence that the pedagogical framework offered a valuable learning experience as they holistically dealt with various stages in BA (Jeyaraj, 2019). Data driven decision management describes a management style in which decisions are directed by hard, verifiable data (Bullard, 2022). As data-driven decision-making has gained prominence within organizations, the need to develop and equip business professionals with skills in BA has gained significant momentum (Provost and Fawcett, 2013). BA courses that address the need to impart skills in acquiring, analyzing, and visualizing data are crucial for the success of business professionals (Waller and Fawcett, 2013; Asamoah, Doran, and Schiller, 2015). McElheran & Brynjolfsson (2016) found that data driven decision making in US manufacturing nearly tripled between 2005 and 2010, from 11% to 30%.

A typical decision-making model starts off with a precise definition of a problem to be solved (or a decision to be made) and ends with a solution to the problem defined. For a data driven decision making, there are three other activities that come in the middle – data, analysis, and results. This was the basis of our preliminary model. The roots for this model can thus be traced back to Dewey's model on decision making which was further structured/detailed by Simon (Dewey, 1910; Simon, 1977). Our model was further refined with concepts from a variety of models – CRISP-DM, SEMMA, and KDD models.

The model developed by us is presented in Figure 1.

FIGURE 1
CONCEPTUAL MODEL OF DATA DRIVEN DECISION-MAKING PROCESS



The model consists of the following:

- Five basic processes – defining the business problem, data, analysis, results, and solution to the stated problem

- Two sub-processes/activities for each of the first four basic processes (numbered 1 through 8 in the model) and the questions to be answered (or issues to be addressed) for each of these sub-processes are listed in Table 2.
- Connections between different processes/sub-processes.

The conceptual model we developed maps well with Simon's decision-making model. The mapping of our model with that from Simon is presented in Table 1.

TABLE 1
MAPPING OF SIMON'S DECISION-MAKING MODEL WITH OUR CONCEPTUAL MODEL

Simon's model	**Our model**
Intelligence (problem recognition/statement)	Sub-processes 1 & 2 Sub-processes 3 through 6 & then 1 & 2 (Exploratory Data Analysis)
Design (generating alternative solutions)	Sub-processes 3 through 6
Choice (selecting the best solution)	Sub-processes 7 & 8 and then 1 & 2

The five basic processes are commonly approached in a sequential manner, in most problem-solving situations. It is also Simon's argument that the three processes/phases (the intelligence, design, and choice) are followed in a sequential manner and within each phase there could still be the same three processes as each phase/process is explored (Simon calls it wheel-within-wheels). However, whenever we get stuck in any of the processes, we will most likely loopback to previous step(s) to continue the problem-solving process. For example, if we cannot get the data, we need to solve the problem as stated in sub-activity 2, we may have to loop back to step 2 and redefine the problem so that appropriate data can be obtained to solve the problem. Also, in some cases, the decision-making activity need not start with the first process. For example, in identifying a problem or an opportunity, we may have to do some exploratory data analysis (EDA) and, hence, the decision-making process may start with data and proceed with the analysis processes sequentially and then loop back to problem statement. Thus, the model has the flexibility to be used in decision making contexts where exploratory or confirmatory data analysis is appropriate.

TABLE 2
EIGHT SUB-PROCESSES – QUESTIONS AND RELATED ISSUES

1. Are we defining the right problem? a. How do we know we have defined the right problem? b. Who would know that? c. Are there processes that would assure us a definition of the right problem? d. Biases in human decision-making (see Tversky & Kahneman's work & Mintzberg's work) e. Note: A problem well defined is half solved (thus it is important to spend considerable time and resources in this activity)
2. Are we defining the problem right? (redefining the business problem stated in sub-process 1 as an analytics problem) a. How do we know we have defined the problem right? b. Who would know that? c. Have we clearly specified the boundaries of the problem? d. Have we understood "what is the problem" and "what is not the problem?" Have we stated them? e. Have we considered all assumptions made (whether implicit or explicit) and stated them? f. Are there processes that would assure us a definition of the problem right? g. Are all the relevant variables identified?

3. Do we have the right data?

a. How do we know we have the right data?
b. Have we defined all the variables needed?
c. Have we coded the data correctly?
d. Have we defined all the variables fully?
e. Are there processes that would assure us a complete set of variables needed to address the problem defined?
f. Are we collecting the specified data using proper methods?
g. Have we used proper verification methods to assure good quality data?

4. Are we using the data right?

a. Have we clearly classified the data into proper categories based on the measurement scale? (qualitative & quantitative, categorical & continuous, etc.)
b. How are we handling missing values in the data set?
c. How are we handling outliers?
d. How are we handling incorrect data?
e. Which variables will be transformed & which transformation technique is right?

5. Are we doing the right analysis?

a. Do the analysis techniques match the data available?
b. Would the results of the analyses address the problem defined in step 2?

Here we can bring in discussion of confirmatory and exploratory data analysis (we can also discuss epistemology of Leibniz and Locke as they relate to confirmatory and exploratory analysis)

6. Are we doing the analysis right?

a. Have we transformed the data, if necessary, correctly?
b. Have we specified the analysis fully and properly for the tool used?
c. Are we using the right techniques to analyze the data?
d. Are we using the intermediate results from the analysis to re-specify the model correctly for further analysis?

7. Do we have the right results?

a. Have we verified the validity of the assumptions for the analytical techniques used?
b. Have we asked for the right and complete outputs from the analyses?

8. Are we interpreting the results right?

a. Are we interpreting the analysis results correctly? How would we assure this is happening?
b. Do we need expertise from others to interpret the results?

Note: This is not an exhaustive list, just a suggested one.

For each of the first four basic processes, we can define two sub-activities. For example, when defining a business problem, we need to ensure that the right problem has been defined and the problem has been defined right -- if we do not do this well, a type III error may occur, i.e., solving the wrong problem. For example, “how to retain customers” may be the right problem to solve, but “how to retain valuable customers” would be stating the problem right. The likelihood of recognizing and defining the problem right depends on understanding the problem domain. Getting input from the stakeholders with different background is very important in defining the problem right. The same structure also applies to data (having the right data versus using the data right – for example, the zip code, inventory number, and customer number data may be the right data, but using that data as quantitative/continuous data in the analysis will lead to wrong results), analysis (doing the right analysis versus doing the analysis right – doing the right analysis is a function of the data and the problem posed, but doing the analysis right is a function of the tools), and results (getting the right results versus interpreting the results right – for example, getting R^2 as a part of the regression analysis results is correct, but interpreting the value without paying attention to the “p” value would be inappropriate).

The connections between sub-activities and between some sub-activities and the first and last basic processes is also important for most decision-making situations. For example, the connection between (sub-activities) 4 and 5 is critical to understand. We may specify the data right but fail to identify the right analysis to be done. We can see this in student work where quarter (with values assigned as 1, 2, 3, & 4) or zip codes are used in the analysis as quantitative variables.

Application of the Model

Once the model is well understood and is deemed acceptable for course development, the focus will be on the following tasks:

1. Determining the depth of coverage for each aspect of the model (the processes and sub-processes) – this could differ depending on the philosophy of the designer of the course. For example, there may be courses where 10-20% the course time be spent on discussion of "data" and some other courses where the coverage may be only 5% of the course time. This also depends on the breadth and depth of students' preparation leading to this course.
2. Identifying and selecting the right course materials that map with the model – this could very well mean that a standard textbook may not be available. Using articles, from academic journals as well as from trade publications, articles that are classics (and possibly dated), and also current articles addressing relevant issues would be appropriate here.
3. Developing/selecting appropriate homework, case analyses, exams, and projects that map well with the model and with prior items 1 and 2. This could mean modifying existing materials (from textbooks) to match the model and its emphasis and also developing new materials as necessary.
4. Developing class discussion materials (like presentation materials) that map well with the model and addresses the questions raised in Table 2.
5. Choosing the right tools for analysis (like Excel, Minitab, SAS/JMP, Tableau, etc.)

The model can be used to develop any introductory BA course, in an MBA program, with different amount of focus on different aspects of analytics – descriptive, predictive, and prescriptive. We believe that the model may not change substantially in the near future, but different users could modify, add, or delete some questions raised in Table 2 to customize the model to their context and needs.

Implementation of the Model

Our implementation context was a redesign of an "applied business statistics" course into an introductory analytics course in the MBA program. However, the model can be used to develop a new business analytics course in MBA programs. As the MBA program already had a "management science" course in the program, the focus of the new course was on descriptive and predictive analytics. This appears to be the case with most existing introductory business analytics courses in MBA programs as we have noted in the summary of the meta-analysis of syllabi. The designer was given complete freedom in forming the course and the designer exercised the freedom in making sure the content from the existing course did not have an undue influence on the new course. Though some topics overlap between the two courses, the emphasis shifted from "teaching business statistics" to "solving business problems using statistics." The new course was named "data driven decision-making" and all content (the breadth and depth) as per the model was specified before selecting the course materials (like books, articles, cases, etc.). Due to the design of the course, a traditional business statistics book or an available business analytics book was deemed to be unsuitable.

The main issue that had to be considered during the design/development of the course was the fact that many adjunct faculty would be teaching this course. Therefore, training was required to prepare them and make them comfortable teaching a radically different course compared to a traditional applied business statistics course that they were used to teaching. Also, new materials to suit the new course had to be developed – materials such as case studies, exams, projects, homework sets, etc. The materials were developed (or modified from existing materials) so that they can be mapped with the processes and sub-processes discussed in different sessions (again, with an emphasis on "solving business problems using statistical techniques" always in the forefront of discussion). To enforce the use of the DDDM model, each assignment required the students to use the following structure to address business problems:

a) State the business problem in plain English
b) State the equivalent statistical problem that addresses the stated business problem
c) Identify and list all the necessary variables needed to address the stated statistical problem
d) List all the data available to address the statistical problem
e) Present the Minitab results
f) State the statistical conclusions (drawn from the Minitab analysis)
g) State your business conclusions/recommendations in a short paragraph or memo in plain English.

The course was offered in an eight-week format, one 4-hour session per week for eight weeks (with a stated expectation that students spend an average of 18 hours outside the classroom per week on the course). The course was offered for the first time in Nov-Dec 2018, when it was taught in both online and on-the-ground versions. Some relevant parts of the syllabus developed – like course learning outcomes, reading materials, and course schedule/outline – are listed at the end of this paper.

LESSONS LEARNED AND IMPLICATIONS

Some lessons learned from the first delivery of the course – with experience of one of the authors, feedback from six adjunct faculty who taught the course and a little over 100 students are presented next.

- The model makes new course development considerably focused and straight forward.
    - It assisted the faculty involved in focused discussions on specific processes and sub-processes to be included in specific sessions. It helped faculty plan class sessions and spend appropriate amounts of time/emphasis on chosen topic areas. The model does not restrict academic freedom of faculty (in delivering the course) as long as they meet the course learning outcomes as stated.
- Students, in general, appreciate the business problem (or application) oriented focus of the course. They also appreciate the context discussions in the practitioner book assigned (Ayres, 2018).
    - Many students specifically commented on the usefulness of the "solving business problems" focus and indicated that they have started using the concepts/tools at their place of work.
    - Students also had positive comments on the "practitioner oriented" reading materials (instead of boring academic materials).
- Do not overwhelm the students with reading materials – select/assign weekly materials that require reasonable number of hours to finish. Our students are expected to work outside the classroom an average of 18 hours per week/session. Providing "practitioner oriented" course materials, and having an emphasis on "solving business problems" makes the readings a bit more enjoyable and hence desist students from complaining about hours spent outside of course seat time per week.
- Do not overwhelm the students with too many analysis tools. We eased the students into using these tools with tutorials developed specifically for this course. Our students appreciated this extra help they received.
- Work closely with students needing extra help by providing them timely, appropriate and adequate tutorial help. As the course is fairly intense for most students, and as the course material is somewhat sequential in nature, it is important to diagnose the need for, and provide timely tutorial help to students who are having some difficulty with concepts, or tools in the course.
- A segment of students has difficulty connecting the five basic processes correctly. This was evident in the difficulty of some students with the project where they were required to pose a

business problem and take it through an analytic solution. Thus, it is important to emphasize (in almost every session of the class – in our case just eight sessions) the seamless connections between the processes and sub-processes. It is best illustrated through business examples.

- As part of course assessment, a quiz as a part of the final exam was administered to all students. This consisted of six multiple choice questions – one question on problem solving process using hypothesis testing, one question on interpretation of a confidence interval estimation, and four questions of matching data with the right analysis (different types of data and different analyses). The assessment results are comparable with results from the original applied business statistics course that formed the basis for the new course. This assessment will help us with continuous improvement in the delivery of the course.
    - Anecdotal evidence volunteered by students indicate their clear happiness regarding the decision-making focus of the course and the usefulness of the course content. This is a very positive indication that the course was well received. It is very rare indeed when a student in a quantitative course voluntarily provides positive feedback!

The main implication for the course design using our model is to start with a simple design of the course (that does not overwhelm the students) and slowly add more content (i.e., readings, assignments, tools, etc.) over several deliveries of the course. In our program, this course is a pre-requisite course (and hence can be waived for students with a business degree). The diversity in the classroom is considerable with student age range of 22-55 years. This also results in considerable diversity in work experience. This will always be a challenge in course design/delivery. The implication we have discussed may be more or less severe depending on the composition of the student group.

Though the model may seem to indicate a sequential decision-making process (as laid out), it is important to note there may be exceptions depending on the context. For example, in “big data” environments, the data already exists and hence the process starts with analysis (i.e., sub- process 5) and then eventually loop back to the “business problem” process. In other situations, regulatory requirements/standards, for example in healthcare environments, may constrain available data. This may again lead to starting with the “analysis” process of the model instead of the “business problem” process.

CONCLUSION

In this paper, we demonstrated how a conceptual model of the data driven decision making process can guide in developing a graduate introductory BA course in the MBA program. This approach will help faculty in developing a BA course that is focused & consistent in course content. This well-defined data-driven decision-making process enables the faculty to break down complex problems into smaller steps that are easy for students to understand and master. This will also help students to get a clear grasp of the business problems to be solved. This can also help book publishers develop BA books that are based on a standard and systematic process for BA. This should help faculty and publishers develop better course materials such as exercises, projects, cases, and discussion materials. The model presented in this paper is not rigid and provides flexibility to faculty teaching the BA course on the amount of time and coverage of topics in each phase of the data-driven decision-making process. The use of this model in refining the courses developed and in developing new courses will provide data for validation of the model/approach presented. Though the processes/sub-processes of the model developed are typically approached sequentially, it is important to note that exception to this is very much possible. An example of this could be the exploratory data analysis that could be used to identify problems. This would typically start with the “data” process and sub-processes 3 & 4, proceed with “analysis” process and sub-processes 5 & 6 and then loop back to “business problem” process.

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APPENDIX

Course Learning Outcomes

1. Upon successful completion of this course, students will be able to:
2. Identify organizational opportunities for data-driven decision-making that create value.
3. Define each opportunity clearly and accurately and articulate why your definition is right.
4. Specify the data needs for each opportunity identified, including its collection, and justify how that data is relevant for the context.
5. Identify and justify the right data analyses that could support decision-making in the context of the opportunity and data needs specified.
6. Perform relevant analyses using the right business analytics (BA) tools.
7. Effectively communicate the findings of the analyses performed to the decision maker(s).
8. Evaluate and articulate the value delivered by data-driven decision-making, for each opportunity identified.
9. Evaluate the ethical implications associated with BA use in organizations to assist decision making.

Readings: Textbooks

1. Diez, David M, Barr, Christopher D, and Mine Cetinkaya-Rundel. (2017). OpenIntro Statistics (Third edition). Openintro.org. Use the following link for a free download: https://www.openintro.org/stat/textbook.php.
2. Tufte, Edward (1997). Visual and statistical thinking: Displays of evidence for making decisions. Cheshire, CT: Graphics Press. ISBN-10: 0-9613921-3-4; ISBN-13: 978-0961392130.
3. Ayers, I. (2008). Super Crunchers: Why thinking-by-numbers is the new way to be smart. New York, NY: Bantam Books. ISBN-10: 0553384732; ISBN-13: 978-0553384734
4. Davenport, Thomas H, and Jinho Kim. (2013). Keeping up with the quants. Boston, MA: HBS Publishing. ISBN-13: 978-1-4221-8725-8

Readings: Required Articles

Session	Article description
1	1. Buchanan, Leigh and Andrew O'Connell (2006). A brief history of decision making. *Harvard Business Review* (January), 32-41. 2. Chottiner, Sherman, "Statistics: Toward a Kinder, Gentler Subject," *Journal of Irreproducible Results*, Vol. 35, No. 6. 3. Frick, Walter (2014). An introduction to data-driven decisions for managers who don't like math. *Harvard Business Review* (May), Accessed on 5/7/2018 from https://hbr.org/2014/05/an-introduction-to-data-driven-decisions-for-managers-who-dont-like-math 4. Hammond, John S, Keeney, Ralph L, and Howard Raiffa (2006). The hidden traps in decision making. *Harvard Business Review* (January, 118-126. 5. Liebowitz, Jay (2015). Intuition-based decision-making: The other side of analytics. *Analytics Magazine* (March/April), 38-43. 6. Lindsay, Matt (2017). The devil is in not having details, so get granular. *Analytics Magazine* (January/February), 8-12. 7. Mehrotra, Vijay (2017). Problem-solving: Keep it real with gemba. *Analytics Magazine* (May/June), 12-15. 8. Michelman, Paul (2017). When people don't trust algorithms. *MIT Sloan Management Review* (Fall), 11-13. 9. Mintzberg, Henry and Frances Westley (2001). Decision making: It's not what you think. *MIT Sloan Management Review* (Spring), 89-93. 10. Rigby, Tom (2017). Survey Sampling. *Analytics Magazine* (November/December), 44-49. 11. The Onion, "U.S. Population at 13,462," April 5, 2000, retrieved on 2/9/13 from https://politics.theonion.com/u-s-population-at-13-462-1819565581
2	Hymowitz, Carol, "**IN THE LEAD: Grading systems force bosses to honestly assess performance**," *The Wall Street Journal*, May 15, 2001.
3	13. Gould, Stephen Jay, "The Median Isn't the Message," *Discover*, June 1985. Retrieved on 5/7/2018 from http://www.phoenix5.org/articles/GouldMessage.html 14. Harvard Management Update (2006). Five Guidelines for Using Statistics. (May 22). Retrieved on 5/17/2018 from https://hbswk.hbs.edu/archive/five-guidelines-for-using- statistics#1 15. Berinato, Scott (2016). Visualizations That Really Work. *Harvard Business Review* (June). Retrieved on 5/7/2018 from https://hbr.org/2016/06/visualizations-that-really-work?referral=03758&cm_vc=rr_item_page.top_right 16. Davenport, Thomas D (2006). Competing on analytics. *Harvard Business Review* (January), 98-107. 17. Dhebar, Anirudh (1993). Managing the quality of quantitative analysis. *Sloan Management Review* (Winter), 69-75. 18. Duarte, Nancy (2014). The quick and dirty on data visualization. *Harvard Business Review* (April 16). Retrieved on 5/7/2018 from https://hbr.org/2014/04/the-quick-and-dirty-on-data- visualization?referral=03759&cm_vc=rr_item_page.bottom 19. Nickell, Joe Ashbrook (2002). Data mining: Welcome to Harrah's. *Business 2.0* (April), 48- 54.

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7	32. Kauffman, Elisabeth, and Crab Orchard, "Watch for Huddling Spiders," *Time*, October 19, 1998, p. 6. 33. Samuelson, Douglas A (2011). Assessing the analysts. *Analytics Magazine* (September/October), 8-10. 34. Samuelson, Douglas A (2017). Storytelling: The write stuff. *Analytics Magazine* (May/June), 64-68.
8	35. Siegel, Eric (2013). The privacy pickle. *Analytics magazine* (November/December), 40-45.

Course Schedule (Planned)

DAY/ DATE	TOPIC	TO DO (before you attend that session)	WORK DUE
1.	Introduction to the course: Decision-making (DM), data, patterns, and solution	**Read: Diez et al --** Chapter 1, **Davenport et al** – Chapter 1 **Ayers** – Introduction & Chapter 1 **Articles:** 1-11 **Tufte** – pages 5-15 **Explore: n/a** **Think and come prepared to discuss** sampling and data collection in your organization.	

2.	Uncertainty and patterns in uncertainty	**Read: Diez et al --** Sections 2.1, 2.4, 2.5, 3.1, 3.4.1, & 3.5.2) **Davenport et al** – Chapter 2 **Ayers** – Chapter 2 **Articles:** 12 **Explore:** Excel capabilities related to descriptive statistics (functions & graphs) **Think and come prepared to discuss** how uncertainty is handled in your organization.	Homework set #1
3.	Data, variables, patterns, and analytics	**Read: Diez et al --** Chapter 1 **Davenport et al** – Chapter 3 **Ayers** – Chapter 3 **Articles:** 13-19 **Tufte** – pages 16-31 **Explore:** Explore descriptive analytics features of Tableau **Think and come prepared to discuss** how patterns in data are explored in your organization.	Homework set #2
4.	One variable inference	**Read: Diez et al** – Sections 4.1 – 4.3 **Davenport et al** – None **Ayers** – Chapter 4 **Articles:** 20-27 **Explore:** Explore features related to today's topic in Excel **Think and come prepared to discuss** how inferences using data are made in your organization.	Homework set #3
5.	Two variables inference	**Read: Diez et al** – Sections 5.5, 6.4, & 7. **Davenport et al** – Chapter 4 **Ayers** – Chapter 5 **Articles:** 28-30 **Explore:** Explore features related to today's topic in Minitab **Think and come prepared to discuss** examples of single and multiple variable(s) inferences in your organization.	Take- home mid-term exam;
6.	Multiple variables inference	**Read: Diez et al** – Sections 8.1, 8.2, & 8. **Davenport et al** – Chapter 5 **Ayers** – Chapter 6 **Articles:** 31 **Explore:** Explore features related to today's topic in Minitab **Think and come prepared to discuss** how single and multiple variable(s) inferences are made in your organization.	Homework set #4
7.	Multiple variables inference	**Read: Diez et al** – None **Davenport et al** – Chapter 6 **Ayers** – Chapter 7 **Articles:** 32-34	Homework set #5

		Explore: Explore features related to today's topic in Minitab **Think and come prepared to discuss** analytics use in your organization.	
8.	Ethical aspects of data-driven DM Project presentations.	**Read: Diez et al** – None **Davenport et al** – Chapter 7 **Ayers** – Chapter 8 **Articles:** 35 **Explore: n/a** **Think and come prepared to discuss** ethical and social aspects of analytics use in your organization.	Project presentations; Final exam (in-class)