Business Analytics: Addressing the Real Skill Requirements of Employers

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Abstract

The demand for business and data analysts is growing. The business school is well positioned to offer programs to meet these needs. This paper presents the findings from a study of the existing literature on data analytics job roles, skills required from those roles, and using that knowledge to build better programs. Three different types of articles are included in the design: faculty writing about their personal experiences and observations (faculty voice), data gathered from expert practitioners and other academics (nonresident expertise) and empirical data from online job service platforms (content analysis). The narrative review method is used to integrate these disparate sources of information and deliver cohesive observations.

Keywords: Business analytics, Data analytics, Curriculum design, Job openings, Narrative review

1. INTRODUCTION

The need for business analysts and data scientists is skyrocketing and the number of data analytics jobs is predicted to grow throughout the world. According to the World Economic Forum's Centre for the New Economy and Society (weforum.org, 2018), the 'data analysts and scientists' role has been one of the ten highest job growth areas in healthcare, information and communication technology, financial services and professional services industries between 2013 and 2017. During that same time period, data analysts and scientists' roles were in the top 10 growth areas in seven out of eight global regions. By 2022, 89% of the organizations surveyed in the United States anticipated adopting both organizational and user-level data analytics technologies. Big data, which is data sets are so large and complex that traditional approaches are inadequate to handle the advanced demands, require specialized analytic techniques and tools (Chen, Chiang & Storey, 2012). The demand for these types of data analytics is also evidenced by the increasing number of job openings posted through online placement services such as Indeed, Monster.com and LinkedIn.

From an academic viewpoint, data analytics related fields are barely out of their infancies. Professionals in these fields are polymaths well versed in advanced, varied knowledge and skills which have historically been located in universities across the schools of business, computer science, engineering, information sciences, mathematics and statistics. Data analytics projects are by their very nature cross or multi-discipline which creates a challenge for the academy to determine where to best locate data analytic degree programs within the

institution. Universities are racing to retool and deploy both their graduate and undergraduate program offerings which are designed to address these emergent resource requirements.
As scholars struggle to determine the content and nuances of specific programs, and practitioners vie to find prospective employees with the right knowledge, skills and abilities (KSAs), a number of research methods have been employed to help determine the optimal competencies for a particular type of program. Three of these methods are 1) drawing upon the collective voice of the faculty (i.e. their knowledge and experience), Table 1; 2) seeking the guidance of nonresident experts (i.e., not coworkers), Table 2; and 3) content analyses of actual industry needs revealed in job postings, Table 3.

This paper reviews and analyzes exemplar studies of the three methods of determining the KSAs required of business analysts and data scientists. The analysis yields a narrative review that incorporates specific types of jobs, different facets of analytics, and categories of knowledge and skills necessary to perform the specific work demanded across various job roles. The methods of gathering and analyzing data are also compared and contrasted to determine if the source of the information is itself biased. This narrative highlights the various knowledge and skill taxonomies found in the individual studies. These taxonomies, developed over time, are not necessarily contradictory, but are somewhat inconsistent in language, depth, and breath. The results of the present study help address knowledge and skill gaps between what prospective employees may possess with the needs that employers have by informing the curricular design of specific types of data analytics programs at graduate and undergraduate levels. Additionally, this is a step toward developing a more consistent language to aide in the improved identification and placement of new employees in varied types of analytics positions.

2. LITERATURE REVIEW

The proliferation of the data analytics related programs is still a relatively new phenomenon. In the literature, there are relatively few scholars describing their own data analytics curriculum or the curriculum of others. Curriculum development is a multifaceted challenge. In addition to issues of implementation, curriculum designers need to consider questions of purpose such as "what competencies (knowledge, skills and abilities) should students have at graduation?" and "what should the relative emphasis be among those competencies?" In this section, we review the key studies that examine required competencies in the data analytics field that should inform data analytics curricula. Some of the studies reviewed focus on existing information systems curricula and how analytics can be introduced into that discipline, while others help to solidify an often-nebulous distinction among job titles, such as business analyst and data scientist, and skills required for such roles.

Faculty Voice
To keep up with the explosion of data analytics across all industries, colleges and universities have started debuting dozens of data analytics programs during the past few years. Thus, there has been considerable exploration and experimentation in creating data analytics courses to provide the requisite students competencies. In this vein of research, scholars and faculty reflect on their knowledge and experience in the data analytics ecosystem. Many scholars believe that the information systems faculty should retool and transform their curriculum into a data analytics major (Urbaczewski & Keeling, 2019). Mortenson, Doherty, & Robinson (2019) suggest that business schools typically house business (data) analytics programs and courses in business analytics should be directly aligned with the needs of industry. Therefore, it is advisable to include industry experts during program design and also to require real-world projects in the curriculum (Wymbs, 2016; Chiang, Goes, & Stohr, 2012).

New graduate-level business analytics degree program offerings outweigh the introduction of new undergraduate majors. Focusing on graduate curriculum Chiang et al. (2012) suggest that the information systems (IS) discipline is versed in the knowledge and skills needed to prepare both the data specialist and business analyst and the IS discipline would be well positioned to create curriculum that integrates three essential knowledge and skill areas in business intelligence and analytics: 1) analytical skills, 2) information technology knowledge and skills and 3) business knowledge and communication skills. Wilder & Ozgur (2015) expand these areas to five: 1) data management, 2) analytical techniques, 3) result deployment, 4) project life cycle, and 5) a functional area. Skills such as results deployment, project life cycles and functional areas require business and communication skills. Thus, it is critical that business context remains a central component in

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the curriculum of analytics programs located in the business school (Urbaczewski & Keeling, 2019).

Business concepts are not a foundational tenet in all analytic programs. For example, Kang, Holden, & Yu (2015) introduced four Pillar of Analytics on which The Rochester Institute of Technology's Master of Science in Information Sciences and Technologies (IST) was built. Pillar one is Data Preprocessing, Storage & Retrieval. Courses in this pillar focus on unstructured data. Pillar two is Analytical Models and Algorithms where courses focus on extracting knowledge using analytic techniques. Pillar three is Data Exploration where students hone their analytical, data organization and visualization skills. The final pillar is Data Product where courses require students to work in teams and draw upon previous course content in developing a well-thought-out project.

In undergraduate-level programs, scholars claim the focus of business analyst development should be both on applying analytic techniques and communicating the implications of those results to management. Subsequently, with the emphasis on business and communication, the analytical training and technical depth of the business analyst is less than required of a data scientist (Wilder & Ozgur, 2015). Wilder & Ozgur (2015) also discuss the role of 'data specialist'. They view the technical depth of the data specialist somewhere between that of the data analyst and data scientist and describe the data specialist as responsible for storage, access, and analysis of data. Whereas, they suggest the business analyst (p. 181): "*need(s) to be able to identify and exploit opportunities. They need sufficient functional expertise to frame business problems and interpret the results. Business analysts do not need to be experts in the various analytical tools but they need to have confidence in these tools. They simply need to ask the right questions and form the right hypotheses*."

Nonresident Expertise

In order to understand the optimal knowledge and skill set for data analytics programs, authors have also examined business analytics and/or data science curricula, and solicited input of industry and academic experts' through interviews, surveys, and Delphi studies. Some of the studies employed multi-method analyses to explain and validate their results.

Two of the included studies focus on graduate-level programs. The first aimed to validate if curricular choices made by data analytics related programs fill the knowledge and skill requirements of industry. At one university, 166 students in a professional master's program in business analytics, were required to complete a survey describing the type of activities and tools used during their internship experience. Data analysis, data cleaning and visualization were the top three activities reported by 85%, 75% and 75% of the students respectively. These results led the authors to conclude that most business analytics programs do not focus enough on those three areas (Hefley, Parker, & Chatterjee, 2019). This report provides another example of the importance of industries' influence on curriculum design.

The second study used publicly facing websites to analyze the curriculum of 15 graduate programs in business analytics. Their sample showed an increased focus on basic statistics, like predictive modeling. This increased focus on statistics seemed to be at the expense of organizational and managerial concepts, for example project management (Johnson, Albizri & Jain, 2020).

The bulk of nonresident expertise studies, as described below, focused on undergraduate-level programs. Using course syllabi from various universities, Aasheim, Williams, Rutner, & Gardiner (2014) observed a pattern where business school analytics programs are called "business analytics" or "data analytics" and computer science related departments use the "data science" moniker. A second related study noted similarities between the two program types which include: 1) greater math and statistics coverage than typically required for students in each school, 2) more emphasis on data management, 3) courses in data mining, visualization, modeling and analytical techniques, and unfortunately 4) a lack of data ethics and governance. They also observed differences between the business school's data analytics and computer science data science programs which included: 1) more math, statistics, and programing in the data science programs than data analytics, 2) some of the business schools used case studies, computer science did not, 3) visualization's goal was communication in the data analytics programs, but in data science the focus was on different types of visualization, 4) data analytics concentrated on the evaluation of tools and techniques while data science was concerned with the programming required to implement tools and techniques, and lastly 5) where data analytics focused on using data mining techniques, data science was geared toward learning data mining algorithms (Aasheim, Williams, Ruther, & Gardiner, 2015).

A review of program course descriptions showed that the relationship between the traditional IS curriculum and business analytics curriculum within the business school can be difficult to discern. Ceccucci, Jones, Toskin, Hamden, & Leonard (2020) identified 34 AACSB accredited business schools that offered both IS and business analytics undergraduate degrees. For each school, they compared the list of required courses in the IS program to the required business analytics courses and found a 36% overlap in the content at the course level.

Similarly, Mills, Chudoba, & Olsen (2016) examined the undergraduate programs 118 AACSB-accredited schools. They found that instead of creating a new business analytics program, 35% of the schools added one new analytics course to their existing IS major, 15% added two courses, 7% added three courses and 3% added four courses between 2011 and 2016. To provide more clarity about the nature of the new courses, they also categorized all the new data analytics-related courses into one of the four Pillars defined by Kang et al. (2015). Pillar 2 (data exploration) and Pillar 4 (data products) had the greatest number of new courses. Pillar 1 (data preprocessing, storage, and retrieval) and Pillar 3 (data exploration) also experienced growth in the number of courses offered, but to a lesser extent.

The Delphi technique was used as part of a multi-method study by Cegielski & Jones-Farmer (2016). The 27 expert participants were asked "What knowledge, skills, and abilities should be taught in business schools to prepare students for entry-level careers in business analytics?" The method yielded 15 KSA categories. The categories determined by the expert panel, along with categories emerging from a content analysis of 186 online job posting, were used to develop a Likert scale questionnaire which also asked respondents about the KSAs sought in a new hire. The 160 survey responses by members of business analytics forums revealed overall agreement among the three methods.

Stephens and McGowan (2018) examined the websites of undergraduate business schools to benchmark options for their own university's major and minor in business analytics. They identified four challenges when interpreting their findings. First, the disciplinary home of business analytics is not clear. Second, no standardized curriculum model exists. Third, no governing body is responsible for creating a standardized curricular model. Finally, business analytics is not clearly distinguishable from other areas such as data analytics and data science. Subsequently, there seemed to be no consistency across programs in terms of "their approach, program name, courses, required content or any other aspect of the program" (p.77).

Burns and Sherman (2019) purported the value of business analytics as a minor for the undergraduate business student. They perused catalog descriptions of courses found in the curriculum of business analytics minors from 60 schools. Basic statistics was the most common requisite and predictive and descriptive analytics were the most identified topics across the programs. They presented an exemplar curriculum for a business analytics minor comprised of three prerequisite courses (basic statics, principles of IS, and excel), three required courses (business analytics 1, business analytics 2 and management science) and two electives housed within a business discipline.

Content Analysis

At aggregate levels, online job advertisements can be valuable indicators and reveal shifting labor demands as they occur. This can provide policy-makers, curriculum developers and scholars additional data points to assess the dynamics of labor markets. In addition, for millions of workers, online job ads provide the first point of contact to potential employers. As a result, job postings and the competencies listed can significantly affect the makeup of the responding applicant pool.

Real-time labor demand data is useful for understanding the analytics ecosystem. A number of studies have used data analytics related job advertisements retrieved from online platforms to identify the optimal knowledge and skill set for data analytics positions. This research stream is important due to its use of job ads as a source of empirical input as well as a validation of curricular choices when designing a relevant data analytics curriculum.

BI and big data skills were the focus of the Debortolli, Müller, & vom Brocke's (2014) content analysis of 1,807 job advertisements found on Monster.com during 2013 and 2014. They created hierarchical, tree-structured taxonomies of the desired skills for BI and big data jobs. These taxonomies revealed that for successful initiatives, individuals having business skills were as important as having technical skills in both BI and big data jobs. BI skills were in higher demand and more focused on commercial products and vendors than the skills associated

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with big data. Big data skills were more analytical and software development oriented.

Also during 2013 and 2014, an automatic detection and clustering analysis of 924 data analyst job listings from LinkedIn, Indeed and Monster.com, was used to identify five job responsibilities and four skill requirements for data analysts (Luo, 2018). Job responsibilities included: 1) data management, 2) data analysis, 3) insight generation, 4) project management and 5) functional responsibility. Whereas skill requirements included: 1) academic qualifications, 2) soft skills, 3) technical skills and 4) software tools. This study found that when seeking the technical skills associated with data management and analysis, the demand for soft skills decreased. Conversely when seeking candidates for a position of functional responsibility, the need for technical skills declined.

Cegielski & Jones-Farmer (2016) focused on entry-level business analytics positions and pulled 186 job ads from LinkedIn, Career-Builder and Monster.com in 2014. Their KSA framework had three major categories 1) business, 2) analytical and 3) technical skills. They further divided the technical KSAs into applications, languages and infrastructure.

In 2015, Gardiner, Aasheim, Rutner, & Williams (2018) harvested 1,216 job advertisements containing 'big data' in the job title from Indeed. Using automatic topic detection and expert verification, 218 job skill related terms were identified. These were clustered by experts into 24 KSAs. Business and soft skills, such as communication, domain, leadership, personal skill attributes and team, prominently resided among the technical skill categories. Thirteen percent of the 218 job skill terms fell within one of the aforementioned soft skill categories. The importance of data analytics roles requiring strong business acumen is also indicated in the analysis of 2,786 job listings scraped from Dice.com during 2015 (De Mauro, Greco, Grimaldi, & Ritala, 2018). In this study, a skills matrix was utilized to map the relevancy of each skill set to one of the business analyst, data scientist, developer or engineer job categories. The business analyst role was most tightly associated with project management and business impact skills. The data scientist's strongest skill set was typically analytics, but business impact and database management also ranked highly. The developer had the greatest association with coding, but cloud, systems management, and distributed computing ranked high. Finally, the engineer role was most associated with architecture skills and to a lesser extent cloud, systems management and distributed computing.

December 2016 through February 2017, Verma, Yurov, Lane, & Yurova (2019) scraped 1,235 job advertisements for 1) business analyst, 2) BI analyst, 3) data analyst and 4) data scientist from Indeed. For each of the job roles, they identified the five most frequently referenced skill categories found in the job ads. Across all four job types, decision making skills were most frequently mentioned skill set. Organization skills (e.g. teamwork and management) was always in the found in top three types of required skills. Statistical skills was conspicuously missing from the business analyst ideal profile, but it was the data scientist's second most frequently mentioned skill set. Programming skills was only mentioned in the data scientist's top five. Note that both the business analyst and data scientist, alone, had domain skills (i.e., the business context) among their top five most required skill sets. This study demonstrated the overlapping skill sets of job roles while emphasizing the varied intensity of skill requirements within job roles.

Radovilsky, Hegde, Acharya & Uma (2018) collected 1,050 job postings from either LinkedIn, Indeed, Glassdoor, Monster.com and Careerbuilder.com during 2017. Their objective was to add more clarity to the distinction between a data scientist and a business data analyst. This study generated lists of the 20 most frequently mentioned words associated with data scientist and big data analyst job ads and categorized them into four knowledge domains: technical, analytical, business, and communication.

Mortenson, et al. (2019) looked at master's level analytics programs in the UK to determine what other disciplines were most closely aligned with analytics offering. Using both job advertisements (n=8,846) and course descriptions (n=234), they applied clustering analyses to develop a model to predict courses for specific analytic-type programs. The first type of master's program aligned with machine learning and was primarily housed in computer science related programs. The second type of program most closely aligned with operations research and was found in business programs.

Johnson, et al. (2020) scraped 5,257 business analyst related entry-level job postings from Indeed.com in 2018. The results from the web scraping were subsequently validated by surveying experts and focus groups. Their result confirmed the need for graduate-level programs, SQL, Python and R were key tools, graduates should have some knowledge of big data platforms, and both analytical and soft skills were required.

Persaud (2020) used Le Deist & Winterton's (2005) Holistic Model of Competence to frame the competencies required of big data analytics professionals. The Holistic Model of Competence identified three distinct types of competencies: cognitive, functional and social. At the nexus of these is meta-competence, which represents the KSAs needed to address messy, complex challenges. Using text mining on 3,009 job postings for data analytics related positions from Indeed, LinkedIn, Monster.com, Procom and also the related academic program materials from 61 Canadian universities and colleges, he identified four broad KSA categories. Technical KSAs, which fall into the cognitive and functional competences were 1) data analytics and 2) computing. The social and meta competences were 3) business and 4) soft skills.

A study that compared the analytics skills listed in 3,511 U.S.-based job advertisements from Monster.com and Indeed.com posted between October 2018 and January 2019 with skills taught at 1,079 courses across the 49 graduate programs concluded that graduate business schools are placing too much importance on highly technical topics that would be better placed in data science programs (Seal, Leon, Pryzasnyski & Lontok, 2020).

3. METHODOLOGY

Narrative review is one of many ways to summarize, integrate and interpret selected sets of scholarly works in various fields. Narrative reviews present verbal descriptions of past studies focusing on frameworks and theories, and/or research outcomes (King & He, 2015). While no commonly accepted or standardized procedure for conducting a narrative review exists, with regard to data analysis, narrative summary refers to the informal techniques used to synthesize prior study findings, often including some type of commentary or interpretation (Dixon-Woods, Agarwal, Jones, Young, & Sutton 2015). In its simplest form, the narrative review attempts to identify what has been written on a topic (Pare, Trudel, Jaana, & Kitsiou, 2015) with the goal of coming to some conclusions through classifications of the research methods and categorizations of results.

Identifying and Selecting Studies

The narrative review process starts by identifying studies. To identify these studies, we used Google Scholar and the online databases accessible via our university. Using the search feature, we fixed the criteria of the research to include 1) exact phrase = "data analytics", 2) at least one of terms = "job postings" or "job ad" and/or curriculum. The keyword combination of data analytics and job postings/ads returned 469 results (conducted June 21,2020). An author of this study manually evaluated each of the items and eliminated all items that 1) were not journal articles, 2) did not contain online job posting data, and 3) were not accessible in English. Most of the 469 items that were identified in the initial search focused on other research questions such as non-data analytic jobs, data analytic powered recommendation systems, using data analytics to facilitate minority hiring and to eliminate AI introduced bias for candidates from underrepresented populations, social networking effects on hiring patterns and building intelligent recruiting tools. To increase confidence in the identification of relevance studies, each paper's literature review and bibliography were examined for candidates for inclusion. The final list was pared down to 12 journal articles containing the results of a content analysis of data analytic-related job postings.

The keyword combination of data analytics and curriculum returned over 15,000 results. In order to select exemplary work from the result list, we selected most commonly cited studies and applied the same elimination criteria as above (journal article accessible in English). We then examined the references of remaining studies and pared down our list to 15 articles that discuss data analytics curriculum development. We then used the bibliography of cited articles to identify other papers that contributed to the development of the studies using actual job posting data.

Coding and Analyzing Studies

This step is focused on the extraction of the information from each study selected. To accomplish this task, we use an excel table with the coded study criteria such as publication date, authors, data source and dataset size. When coding the studies, we first classified them into three principal categories representing different methodologies used: 1) conceptual studies drawing upon the collective voice of the faculty (i.e. their knowledge and experience), 2) curriculum studies seeking the guidance of practitioner experts, and 3) content analyses of actual industry needs revealed in job advertisements.

Tables 1, 2 and 3 presented in Appendix A summarize the articles included in our review. Table 1 shows the conceptual studies representing faculty voice. Faculty experience, discussions and literature review were the basis for these papers. Table 2 shows the studies that examined business analytics and/or data science curricula, and solicited input of industry and academic experts. These studies present primary and/or secondary data. Table 3 presents studies that gathered new, original data collected through web scraping and content analysis of online job advertisements.

4. RESULTS

Although the data analytics field has been one of the highest growing job areas during the last decade and many universities are designing and retooling their programs and curricula to include data analytics skills, there is to-date no systematic review of recent job advertisement studies with the focus of integrating data analytics skills into curricula. In reviewing past studies, we make five observations.

First, the dearth of earlier studies emphasizes that the field is relatively new and growing in importance. Second, most studies emphasized that there were a large number of different job titles for data analytics related roles (e.g. 55 jobs titles in Stanton & Stanton, 2015). The most frequently occurring listings were for data scientists, data analysts, and business analysts (e.g. Debortolli et al., 2014; De Mauro et al., 2018, Verma et al., 2019; Persaud, 2020).

Third, the descriptions of the required skills and responsibilities of these roles were often found to be similar and were most commonly grouped into three major categories: business /analytics / technical (e.g. Radovilsky et al., 2018; Chang et al., 2018) or hard/soft/software (e.g. Luo, 2016; Stanton & Stanton, 2020). These similarities between the job roles necessitate faculty invest in defining the mission, goals, objectives and scope of their specialized programs. Part of this effort is understanding the how one academic unit's offering is different than another's. Although there seems to be a great deal of overlap in topics among both graduate and undergraduate programs, found in units such as computer science, mathematics, information science and the business school, each program has unique strengths that differentiate it from other disciplines. It is the breadth and depth of topic coverage, varying often by discipline, that distinguishes one program from another. For example, it was shown that business schools tend to use the "data analytics" or "business analytics" moniker, computer science schools preferred "data science" as a label (Aasheim et al., 2014; Aasheim et al., 2015). Business analyst is typically the least technical job role (Verma et.al., 2019). And business analysts, compared to more technical "data scientist" roles, tend to have more functional responsibility, project management experience and insight into the business impact of analytics driven decision making (Luo, 2016). A skill like project management, is more important to the business analyst because projects are used to execute strategy (De Mauro et al., 2018). Business skills, especially understanding the potential business impact of decisions based on analytical reports, are important to both business analysts and data scientists. With that said, several studies emphasized the importance of business skills, not only for business/data analyst roles, but also for the data scientist and other related positions.

Fourth, the most desirable skills for entry-level analytics positions were found to include data analytics, modeling, and business strategy in the hard skills category; analytical, problem-solving and written communication in the soft skills category; and SQL, Python and Java in the software skills category (Stanton & Stanton, 2019). In addition, junior level employees tended to have more technical skill requirements, whereas senior-level employees needed more business skills to formulate and execute strategy (Chang et al., 2018).

Fifth, big data and big data analytics were among of the most frequently discussed areas in the papers reviewed and many papers included "big data" as their own search criteria when searching for previous literature or related job advertisements (e.g. Debortoli et al., 2014; Gardiner et al., 2018; De Mauro et al., 2018; Persaud, 2020).

And finally, each type of study could be subject to its own unique bias. For example, the voice of the faculty may be constrained by faculty expertise and training. Non-resident experts may be influenced by their peers in focus groups and advisory meetings. The quality of empirical data from web scraping is only as good as the job requirements are accurately described. In other words, are the necessary requirements in the text or could the real requirements be idealized and rarely met?

4. CONCLUSION AND FUTURE WORK

We believe this is the first time a narrative review method has been used to identify, analyze and synthesize key published articles representing the 1) wisdom of academics (faculty voice), 2) expert practitioner and academic input (nonresident expertise) and 3) empirical data from online job service platforms. This effort provides a multi-perspective view of the best practices in the identification of the KSAs of perspective job roles and applying this insight into the development of new data analytics curriculum. With this knowledge, business school faculty will be better informed and able to develop distinctive programs that capitalize on their unique strengths, while simultaneous meeting or exceeding the expectations of their students.

A limitation of this type of study is that it is difficult to match specific low-level skill descriptions to higher-level course topics. Guidance is lacking in addressing this matching problem.

Further investigation is needed to better understand the relative importance of specific skills in securing and employment and job performance. This is necessary for faculty to make better tool choices and decisions about the percent of class time dedicated to specific topics. Multi-method studies are necessary to understand biases in the reported importance of skills. For example, if employers describe what skill levels they want in candidates, do they settle for lessor skills because of a perceived lack of skills among the candidate pool?

5. REFERENCES

Aasheim, C. L., Williams, S., Rutner, P., & Gardiner, A. (2014). Big Data Analytics and Data Science Undergraduate Degree Programs. 2014 Annual Meeting of the Decision Science Institute Proceedings (DSI 2014), 1-22, Tampa Florida.

Aasheim, C. L., Williams, S., Rutner, P., & Gardiner, A. (2015). Data analytics vs. data science: A study of similarities and differences in undergraduate programs based on course descriptions. *Journal of Information Systems Education*, *26*(2), 103.

Burns, T. J., & Sherman, C. (2019). A Cross Collegiate Analysis of the Curricula of Business Analytics Minor Programs. *Information Systems Education Journal*, *17*(4), 82.

Ceccucci, W., Jones, K., Toskin, K., Hamden, C. T., & Leonard, L. (2020). Undergraduate Business Analytics and the overlap with Information Systems Programs. INFORMATION SYSTEMS EDUCATION JOURNAL, 18(4), 4.

Cegielski, C. G., & Jones-Farmer, L. A. (2016). Knowledge, skills, and abilities for entry-level business analytics positions: A multi-method study. *Decision Sciences Journal of Innovative Education*, *14*(1), 91-118.

Chen, C., & Jiang, H. (2020). Important Skills for Data Scientists in China: Two Delphi Studies. *Journal of Computer Information Systems*, *60*(3), 287-296

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS quarterly*, 1165-1188.

Chiang, R. H., Goes, P., & Stohr, E. A. (2012). Business intelligence and analytics education, and program development: A unique opportunity for the information systems discipline. *ACM Transactions on Management Information Systems (TMIS)*, *3*(3), 1-13.

Debortoli, S., Müller, O., & vom Brocke, J. (2014). Comparing business intelligence and big data skills. *Business & Information Systems Engineering*, *6*(5), 289-300.

De Mauro, A., Greco, M., Grimaldi, M., & Ritala, P. (2018). Human resources for Big Data professions: A systematic classification of job roles and required skill sets. *Information Processing & Management*, *54*(5), 807-817

Dixon-Woods, M., Agarwal, S., Jones, D., Young, B., & Sutton, A. (2005). Synthesising qualitative and quantitative evidence: a review of possible methods. *Journal of health services research & policy*, *10*(1), 45-53.

Gardiner, A., Aasheim, C., Rutner, P., & Williams, S. (2018). Skill requirements in big data: A content analysis of job advertisements. *Journal of Computer Information Systems*, *58*(4), 374-384.

Hefley, B., Parker, J., & Chatterjee, S. (2019). Entry-Level Data Science Work Practices and Environments. In *Proceedings of the International Conference on Frontiers in Education: Computer Science and Computer Engineering (FECS)* (pp. 134-139). The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp).

ISSN: 2473-4901
v6 n5354

Johnson, M. E., Albizri, A., & Jain, R. (2020). Exploratory Analysis to Identify Concepts, Skills, Knowledge, and Tools to Educate Business Analytics Practitioners. *Decision Sciences Journal of Innovative Education*, *18*(1), 90-118.

Kang, J. W., Holden, E. P., & Yu, Q. (2015, September). Pillars of analytics applied in MS degree in information sciences and technologies. In *Proceedings of the 16th Annual Conference on Information Technology Education* (pp. 83-88).

King, W. R., & He, J. (2005). Understanding the role and methods of meta-analysis in IS research. *Communications of the Association for Information Systems*, *16*(1), 32

Le Deist, F. D., & Winterton, J. (2005). What is competence? *Human resource development international*, *8*(1), 27-46.

Luo, W. (2016). Responsibility and skills requirements for entry level analytics professionals. *Journal of Organizational and End User Computing (JOEUC)*, *28*(4), 1-14.

Mills, R. J., Chudoba, K. M., & Olsen, D. H. (2016). IS programs responding to industry demands for data scientists: A comparison between 2011-2016. *Journal of Information Systems Education*, *27*(2), 131.

Mortenson, M.J., Doherty, N.F., & Robinson, S. (2019): Creating a typology of analytics Master's degrees in UK universities: Implications for employers and educators, *Journal of the Operational Research Society*, DOI: 10.1080/01605682.2019.1605468

Paré, G., Trudel, M. C., Jaana, M., & Kitsiou, S. (2015). Synthesizing information systems knowledge: A typology of literature reviews. *Information & Management*, *52*(2), 183-199.

Persaud, A. (2020). Key competencies for big data analytics professions: a multimethod study. *Information Technology & People*.

Radovilsky, Z., Hegde, V., Acharya, A., & Uma, U. (2018). Skills requirements of business data analytics and data science jobs: A comparative analysis. *Journal of Supply Chain and Operations Management*, *16*(1), 82.

Seal, K. C., Leon, L. A., Przasnyski, Z. H., & Lontok, G. (2020). Delivering Business Analytics Competencies and Skills: A Supply Side Assessment. *INFORMS Journal on Applied Analytics*, *50*(4), 239-254.

Stanton, W. W., & Stanton, A. D. A. (2020). Helping Business Students Acquire the Skills Needed for a Career in Analytics: A Comprehensive Industry Assessment of Entry-Level Requirements. *Decision Sciences Journal of Innovative Education*, *18*(1), 138-165.

Stephens, P., & McGowan, M. (2018). Issues in the Development of an Undergraduate Business Analytics Major. *Issues in Information Systems*, *19*(2).

Urbaczewski, A., & Keeling, K. B. (2019). The Transition from MIS Departments to Analytics Departments. *Journal of Information Systems Education*, *30*(4).

Verma, A., Yurov, K. M., Lane, P. L., & Yurova, Y. V. (2019). An investigation of skill requirements for business and data analytics positions: A content analysis of job advertisements. *Journal of Education for Business*, *94*(4), 243-250.

weforum.org. (2018) Retrieved from http://www3.weforum.org/docs/WEF_Future_of_Jobs_2018.pdf.

Wilder, C. R., & Ozgur, C. O. (2015). Business analytics curriculum for undergraduate majors. *INFORMS Transactions on Education*, *15*(2), 180-187.

Wymbs, C. (2016). Managing the innovation process: Infusing data analytics into the undergraduate business curriculum (lessons learned and next steps). *Journal of Information Systems Education*, *27*(1), 61.

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Appendix

TABLE 1: VOICE OF THE FACULTY ARTICLES

Article	Analysis type	Keywords	Major Categories / Concepts	Curriculum / Takeaways
GRADUATE				
Chiang, Goes & Stohr (2012) grad program, not only business school	speculate on the demand for BI&A in business schools; 1)industry direction; 2) MS offerings	data mining; text analysis; IS education; big data, BI&A; data warehousing	1) analytic skills; 2) IT knowledge & skills; 3) business knowledge & communication skills	▪ challenges for BI&A programs; ▪ role of IS curriculum
Kang, et al (2015) grad program, not only business school	conceptual framework	information sciences & technologies; curriculum, data analytics, database, web technologies	four pillars: 1) data preprocessing, storage & retrieval 2) data exploration 3) analytical models & algorithms 4) data product	▪ courses needed to support pillars
Johnson, Albizri and Jain (2020) Grad program, business	Curriculum analysis	Analytics education; business analytics; curriculum design		▪ focus on basic analytic skills (descriptive and predictive analytics)
UG				
Wilder & Ozgur (2015) UG program, business school	purposed undergraduate business analytics curriculum	business analytics; UG curriculum; business analyst	1) project life cycle 2) data management 3) analytics techniques 4) result deployment 5) functional area	▪ appropriate skill level and breadth of knowledge ▪ for students with average to above-average analytical skills ▪ guidelines to ensure success
Wymbs (2016) UG program, business school	recommenda-tions for curriculum design	data analytics; innovation process, curriculum design and development; business relevance		▪ driven by business input & academic leadership incorporating innovation theory & practice concepts
BOTH				
Urbaczewski & Keeling (2019) UG & grad programs, business school	transitioning from MIS to analytics programs	academic degree; IS environment; IS ed; computing education; business analytics; IS ed research		▪ invited paper ▪ reflecting the last decade in the field & the next decade to come

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TABLE 2: NONRESIDENT EXPERTISE ARTICLES

Article	Analysis type Sample Size	Keywords	Major Categories / Concepts	Curriculum / Takeaways
GRADUATE				
Hefley, et al. (2019)	Internship experience survey; 166 business analytics graduate students	data science; data analytics; work practices; environments; entry-level workers	1) activities 2) coding 3) S/W packages 4) s/w tools 5) platforms	▪ focus more on data analysis, data cleaning, and visualization
Johnson, Albizri and Jain (2020) Grad program, business	Curriculum analysis	Analytics education; business analytics; curriculum design		▪ focus on basic analytic skills (descriptive and predictive analytics)
UG				
Aasheim et al. (2014)	skills survey IT managers (350); IT faculty (78)	IS skills; IT skills; skill set; knowledge requirements; IS professionals; IT professionals; curriculum development	1) interpersonal 2) personal 3) technical 4) organizational & managerial 5) experience & GPA	▪ here is no significant difference between faculty's and IT managers' perceptions of average importance.
(Aasheim et al., 2015)	course description content analysis 13 data analytics UG programs	data analytics; job skills; emerging technologies; program improvement	data science programs; data analytics programs	▪ DS requires more math, statistics, programming ▪ DS requires learning data mining algorithms ▪ DA requires using data mining techniques
Cegielski & Jones-Farmer (2016)	Delphi method / skills survey 27 experts / 160 practitioners	business analytics; big data; Delphi method; content analysis; qualitative methods	1) business 2) analytical 3) technical (apps, languages, infrastructure)	▪ 15 KSA categories ▪ all methods agreed
Mills et al. (2016)	curriculum review 118 AACSB UG IS programs	big data; data analytics; visualization; business intelligence; model curricula	Pillars of Analytics (Kang, Holden, and Yu, 2015)	▪ 60% of AACSB IS programs added data science-related courses between 2011 & 2016
Stephens & McGowan (2018) UG program, business school	literature review, curriculum analysis	business analytics; business intelligence; data analytics; data science		▪ no discipline owns BA ▪ no model curriculum ▪ no organization responsible for curriculum model ▪ lacks a clear boundary
Burns & Sherman (2019) UG minor, business school	curriculum analysis	business analytics knowledge and skills' business analytics minor curriculum	1) prerequisite topics 2) required topics 3) elective topics	▪ prerequisites: basic stats, principles of IS; Excel ▪ required: BA 1; BA 2; management sciences ▪ electives (discipline specific)
Ceccucci et al. (2020) UG program, business school	course description content analysis 34 business schools with IS & analytics programs	data analytics; business intelligence; business analytics program	1) analytical skills 2) IT knowledge & skills 3) business knowledge & communication skills	▪ 36% of BA programs and IT programs overlap

TABLE 3: JOB ADVERTISEMENTS – CONTENT ANALYSIS ARTICLES

Authors	**Scrapping Date Job Title**	**Categories**	**Interesting Points**
Debortolli, et al. (2014)	2013-2014 BIA, BDA	business (domain & management) IT (concepts and methods & products)	▪ BIA skills (more focused on commercial products & vendors) ▪ BDA skills (S/W development, statistical oriented, HR intensive)
Luo, 2018	2013-2014 DA	job responsibilities (data mgt, data analysis, insight, proj mgt, functional) skill requirements (academic, soft, technical, S/W)	▪ technical skills of data management and analysis were negatively associated with soft skills
Cegielski & Jones-Farmer (2016)	2014 BA	business analytical technical	▪ validated by a survey of 160 practitioners ▪ indicated priority skills
Gardiner, et al. (2018)	2015 *BD*	24 KSA categories 218 skills	▪ 13% of skill terms are soft skills
De Mauro, et al. (2018)	2015 BA, DS, developer, engineer	4 job categories 9 skill sets (cloud, coding, DB mgt, architecture, sys mgt, distributed computer, analytics, business impact)	▪ business impact - strongly associated with both BA and DS roles
Verma, et al, (2019)	2016 – 2017 BA, BIA, DA, DS	17 skill categories	▪ decision making - most the frequently mentioned skill set ▪ statistical - not a top 5 for BA ▪ domain - a top 5 for DS and BA
Radovilsky, et al. (2018)	2017 DS, BDA	technical analytical business communication	▪ collaborate - the only soft skill in the DS's most frequently mentioned word list
Stanton & Stanton (2020)	2019 DS, DA, BA	hard skills soft skills software skills	▪ suggestions: real-world, certifications, when & how to use techniques, coding, soft skills, state-of-the-art tools
Montenson, et al. (2019)		type 1 degree – data science / big data type 2 degree – business analytics	▪ type 1- aligned with ML - primarily in comp sci ▪ type 2 closed aligned with OR in business
Johnson, Albizri and Jain (2020)	2018 BA (entry level, not mgmt)	tools big data infrastructure technical concepts soft skills	▪ advanced degrees are preferred ▪ SQL, R, and Python are sought after ▪ Inference, sampling and non-sampling errors
Persaud (2020)	2020 BA, DS, DA, data consultant	data analytics computing business soft skills	▪ data scientists alone - not sufficient to give companies a real competitive advantage
Seal, et al., (2020)	2018-2019 BA	soft skills analytic/technical skills	▪ business schools spend too much time on deeply technical topics