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Analytics in the Business School: Insights from the Literature

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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 both the findings from a review of the existing literature on data analytics job roles, skills required for those roles and also feedback from industry experts on findings. 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. This knowledge can be used to build better analytics programs in business schools.

Keywords: Business analytics, Data analytics, Curriculum design & development, Skill requirements, 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 (weforum.org, 2018). The need for data analytics and its applications is also evidenced by the increasing number of job openings posted through online placement services such as Indeed, Monster.com and LinkedIn (Camm et al., 2020).

From an academic viewpoint, data analytics fields are barely out of their infancies. Professionals in these fields are polymaths well versed in advanced knowledge and skills which have historically been taught in universities across the schools of business, computer science, engineering, information sciences, mathematics and statistics. Data analytics projects are by their very nature multi-discipline which creates a challenge in determining where to best locate analytics programs within the institution. Universities are racing to retool and deploy both graduate and undergraduate program offerings to address these emergent employment requirements (National Academies of Sciences, Engineering, and Medicine, 2018).

As scholars struggle to determine the content and nuances of specific programs while concurrently practitioners vie to find prospective employees with the right knowledge, skills and abilities (KSAs), a number of approaches have been employed to help determine the right balance of competencies for particular types of programs. Three of these methods are 1) drawing upon the collective voice of faculty—their knowledge and experience, 2) seeking the guidance of nonresident experts—those outside the immediate academic circle, and 3) examining actual industry needs through content analysis of publicly available job postings.

This paper reviews and analyzes exemplar studies using at least one of the three methods of determining the KSAs required of business analysts and data scientists. This analysis yields a narrative review that incorporates specific types of jobs, different facets of analytics, and categories of required KSAs. 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 KSA taxonomies found in individual studies. These taxonomies, developed over time, are not necessarily contradictory, but are somewhat inconsistent in language, depth, and breadth. A new model depicting the relationships among the three methods is presented. Finally, four executives familiar with their organizations' data analytics and data science requirements provide feedback on the findings of the narrative review. The results of the present study help in identifying KSA gaps between what prospective employees possess and the needs of employers, as well as in addressing these gaps by informing the curricular design of business analytics programs at both graduate and undergraduate levels.

2. BACKGROUND

The last decade witnessed the emergence of data analytics and its utilization becoming an inextricable part of many industries and businesses. As a result, more and more firms are seeking to recruit and hire individuals with analytic skills. For instance, by 2020, PwC estimates there will be over 2.7 million new job postings for data analytics and data science roles (Rivett, 2020). Thus, it is imperative that universities move rapidly to develop new data analytics programs and incorporate data analytics into their existing programs so that graduates entering today's job market will have the necessary skills (Johnson et al., 2020).

Due to the growing popularity and importance of data analytics for organizations, as well as for universities, research projects related to business analytics have attracted considerable interest and attention in the last decade. While many works have been published related to these topics, there is a lack of studies that review, summarize and synthesize the existing research on various facets of business analytics – especially in business analytics education.

For example, Hindle et al. (2020) performed a computational literature review of the business analytics field (4,957 articles) and showed that the number of articles in the period 2000 through 2018 has grown exponentially. While they identified 36 topics through this automated topic modelling analysis, they did not present any review or synthesis of the reviewed articles. Through a bibliometric analysis, Yin and Fernandez (2020) also concluded that literature about business analytics is growing exponentially. In terms of business analytics education, they found that the field of business analytics is interdisciplinary and successful training should involve technical, analytical, and business skills. The only review study on business analytics education we identified was performed by Wang (2015) where 44 research papers related to business analytics were identified using Google Scholar. These papers were reviewed and categorized into five key research foci based on their relevant ideas, findings and contributions. Wang concluded that an articulated framework of knowledge domains and skill sets for analytics professionals is lacking and the research on analytics pedagogical design and learning activities is mainly exploratory or case study oriented. He also suggested that prior studies have considered the perspectives from faculty, current students, and industry practitioners but feedback from new graduates has not been studied.

In addition to including recently published work, the current narrative review further categorizes the existing articles by their source of data. A new model, *Influencers of Data Analytics Curriculum Design*, of the relationships among these types of articles is presented. The new model emphasizes the need to incorporate multiple perspectives in curriculum design.

3. METHODOLOGY

3.1 Narrative Review

A narrative review is one of many ways to summarize, integrate and interpret selected sets of scholarly works. Narrative reviews present verbal descriptions of past studies focusing on frameworks and theories, and 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 et al., 2015). In its simplest form, the narrative review attempts to identify what has been written on a topic (Paré et al., 2015) with the goal of coming to some conclusions through classifications of the research methods and categorizations of results.

3.1.1 Identifying and Selecting Studies in Narrative Review. The narrative review process starts by identifying studies. To identify these studies, we used Google Scholar and the online databases accessible via our university (Business Source Premier, ProQuest Research Library, JSTOR, and ABI/INFORM). 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," 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 relevant studies, each paper's literature review and bibliography were examined for additional candidates for inclusion. The final list was pared down to 12 journal articles containing a content analysis of data analytics 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. Next, we used the bibliography of cited articles to identify other papers that contributed to the development of the studies using actual job posting data.

3.1.2 Coding and Analyzing Studies in Narrative Review. This step is focused on the extraction of the information from each selected study. To accomplish this task, we used an Excel table with the coded study criteria such as publication date, authors, data source and dataset size. When coding the studies, each author 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 capturing the guidance of practitioner experts, and 3) content analyses of actual industry needs revealed in job advertisements. Classification discrepancies were reviewed and resolved in an iterative process through systematic comparison and discussion of the principal categories.

3.2 Executive Feedback Post Narrative Review

To clarify our understanding of the narrative review findings and weigh the efficacy of a business school in developing high-performing data analysts, we asked four high-level corporate executives, whose resumes include heavy experience with the IS function, to comment on their preferences for specific educational backgrounds and skill sets in their business analytics entry positions. Our goal was to better understand what competencies these four companies require in their business analytics entry-level positions (to compare with the findings of the narrative review) and what should be the relative strengths of those competencies. For the purpose of this inquiry, we defined a business analyst as having data analytics responsibilities and a yearly salary between $50,000 and $75,000 (Glassdoor, Inc., 2020).

The corporate executives were asked whether their companies hire business analysts and if they do, what would be the primary responsibilities and activities of those business analysts. We also asked the executives to comment and rank the educational background characteristics of business analyst candidates from most ideal to least ideal (all other characteristics being equal). The candidate characteristics were derived from the studies that were analyzed under narrative review. The corporate executives were also asked to rank the major KSA categories: 1) business knowledge and communication skills, 2) analytical and programming skills, and 3) information technology knowledge and skills. These categories identified in the narrative review from the most important to least important for candidates to be hired for a business analyst position. Finally, the executives were asked to explain what their companies would most likely compromise if a candidate with all the advertised skills was not identified.

4. NARRATIVE REVIEW FINDINGS

The proliferation of data analytics programs is still a relatively new phenomenon. In the literature, there are relatively few scholars describing their own analytics curriculum. Because curriculum development is a multifaceted challenge, curriculum designers need to consider questions of purpose such as “what competencies (KSAs) should students have at graduation?” and “what should the relative emphasis be among those competencies?” With this information, curriculum designers also need to decide whether to create new programs or expand existing programs. In this section, we review key studies that examine required competencies in the data analytics field that should inform curricula in business schools. Some studies focused on existing information systems (IS) curricula and how analytics could be introduced into that discipline, while others helped in solidifying an often-nebulous distinction among job titles, such as business analyst and data scientist, and skills required for such roles. It is common for business schools to use “data analytics” or “business analytics” to describe their programs, whereas computer science schools prefer “data science” (Aasheim et al., 2014, 2015). Given this practice, we will use either business analytics or data analytics to refer to business school offerings, but we will choose the label that more closely mirrors the language found in the original article being referenced.

4.1 Faculty Voice Studies

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 effort invested in course development to ensure students gain the needed competencies. Many scholars believe that IS faculty should retool existing curricula to focus on data analytics (Urbaczewski & Keeling, 2019) while others suggest that a new data analytics major should be developed (Stephens & McGowan, 2018). Mortenson et al. (2019) suggested that because business schools typically house business analytics programs, 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 (Chiang et al., 2012; Wymbs, 2016).

The introduction of new graduate-level business analytics programs has outpaced the number of new undergraduate offerings. Focusing on graduate curricula, Chiang et al. (2012) suggested that the 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 a new data analytics graduate curriculum that integrates three essential knowledge and skill areas: 1) analytical skills, 2) information technology knowledge and skills, and 3) business knowledge and communication skills. At the undergraduate-level, they also proposed expansion of existing IS programs to include a business analytics focused course. Wilder and Ozgur (2015) expanded these essential knowledge and skill areas to five and suggested that new undergraduate data analytics majors, as well as minors and certificates, should include: 1) data management, 2) analytical techniques, 3) results deployment, 4) project life cycles, 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 a business context remains a central component in the curriculum of analytics programs housed in business schools (Urbaczewski & Keeling, 2019).

Business concepts are not a foundational tenet in all analytics programs. For example, Kang et al. (2015) introduced four Pillars of Analytics on which The Rochester Institute of Technology’s Master of Science in Information Sciences and Technologies (IST) updated and expanded a significant portion of its curriculum. Pillar one is data preprocessing, storage and retrieval. Courses in this pillar focus on unstructured data. Pillar two is analytical models and algorithms where courses focus on extracting knowledge using analytics techniques. Pillar three is data exploration where students hone their analytical, data and visualization skills. The final pillar is data product where courses require students to work in teams and draw upon previous delivered course content in developing a well thought-out project.

In undergraduate-level business programs, scholars claim the focus of business analyst development should be both on applying analytics techniques and communicating implications of results to management. With the emphasis of business school programs on business and communication, analytical training and technical depth of the business analyst is less than what is required of a data scientist (Wilder & Ozgur, 2015). Wilder and Ozgur (2015) also discussed the role of “data specialist.” They viewed the technical depth of the data specialist somewhere between that of the data analyst and data scientist, and described the data specialist as responsible for storage, access, and analysis of data. Whereas, they suggested that business analysts (p. 181) "*need 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*."

Table 1 shows the conceptual studies representing faculty voice. Faculty experience, discussions and literature reviews were the basis for these papers.

4.2 Nonresident Expertise Studies

In order to understand the knowledge and skill set required for data analytics programs, extant studies have also examined business analytics and data science curricula, and solicited input from 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 studies focused on graduate-level programs. 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 activities reported by 85%, 75% and 75% of the students, respectively. These results led authors to conclude that most business analytics programs should focus on those three areas (Hefley et al., 2019). This report demonstrates the potential impact of industry on curriculum. The second study used publicly facing websites to analyze the curriculum of 15 graduate programs in business analytics. Results indicated that programs should be developed to focus on basic analytics skills such as descriptive statistics and predictive modeling. However, this increased focus on statistics seemed to be at the expense of organizational and managerial concepts (Johnson et al., 2020).

The bulk of nonresident expertise studies focused on undergraduate programs. Using course syllabi from various universities, Aasheim et al. (2014) observed a pattern where business school programs were called "business analytics" or "data analytics" and computer science departments used the "data science" moniker. A second study noted similarities between the two program types which included: 1) greater math and statistics coverage than typically required for other 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 schools' data analytics and computer science's data science programs which included: 1) more math, statistics, and programing in the data science programs than in the data analytics programs, 2) the use of case studies only by business schools, 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 those 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 et al., 2015). They suggested that gaps in existing programs could be filled by creating data analytics programs as extensions of current IS curricula in business schools and creating data science programs as an extension of current curricula in computer science departments.

Aasheim et al. (2009) conducted a study to determine whether the importance of various skills for entry-level IT workers were perceived differently by faculty than by IT managers and found no significant difference between faculty's and IT managers' perceptions of average importance. Their findings also showed that personal and interpersonal skills were considered more important for entry-level workers than were technical and analytical skills.

A review of program course descriptions showed that the relationship between the traditional IS curriculum and business analytics curriculum can be difficult to discern. Ceccucci et al. (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 et al. (2016) examined the undergraduate programs of 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 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 (analytical models, and algorithms) also experienced growth in the number of courses, but to a lesser extent.

Cegielski and Jones-Farmer (2016) identified 63 undergraduate programs in the general area of analytics and found that these programs seemed to have been generated from three existing sources: 1) operations research and management science, 2) statistics, or 3) information systems (IS). Due to disciplinary foundations, there was considerable variability among programs and their respective course offerings. In order to understand the essential KSAs that an analytics program should include, the Delphi technique was used in a multi-method study by Cegielski and Jones-Farmer (2016). Twenty-seven 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: business education, problem solving skills, SQL query/code writing, software training, problem/process modeling, research skills, data interpretive ability, business communication, systems infrastructure support, data mining, statistical methods training, data visualization, data modeling, data gathering ability, and data warehouse knowledge. These categories determined by the expert panel, along with categories emerging from a content analysis of 186 online job postings, were used to develop a questionnaire about the KSAs sought in a new business analyst. Survey responses of 160 members of business analytics forums revealed overall agreement among the three methods.

Article	Analysis type	Keywords	Major Categories / Concepts	Curriculum / Takeaways
GRADUATE				
Chiang et al. (2012)	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 (expansion of IS to include BI&A course) ▪ develop new program: MS in BI&A, Graduate certificate program
Kang et al. (2015)	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 ▪ updated MS Program in Information Sciences and Technologies ▪ capstone Project using real-life data
Johnson et al. (2020)	curriculum analysis (graduate level BA courses and Indeed entry level BA job description)	analytics education; business analytics; curriculum design	1)programming/Analytics tools 2)big data concepts 3)technical concepts 4)soft skills	▪ focus on basic analytic skills (descriptive and predictive analytics) ▪ develop new MS program ▪ role of advanced degrees (advanced analytics skill, big data and capstone project needed)
UG				
Wilder & Ozgur (2015)	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 ▪ develop new data analytics UG major (minor and certificate possible)
Wymbs (2016)	recommendations for curriculum design	data analytics; innovation process; curriculum design and development; business relevance		▪ driven by business input & academic leadership incorporating innovation theory & practice concepts ▪ expansion of existing CIS and marketing majors (data analytics major/minor)
BOTH				
Urbaczewski & Keeling (2019)	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 ▪ expansion of MIS to include data analytics

Table 1. Voice of the Faculty Articles

Stephens and McGowan (2018) examined websites of undergraduate business schools to benchmark options for their own university's programs. They identified four challenges while interpreting their findings. First, the disciplinary home of business analytics was not clear. While analytics programs were typically hosted in departments of management information systems (MIS) or decision sciences (DS), some of the programs were owned by statistics, marketing and supply chain management. Second, no standardized curriculum model existed. Third, no governing body was responsible for creating a standardized curriculum. Finally, business analytics was 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 undergraduate business students. They perused catalog descriptions of courses found in business analytics minors from 60 schools. Basic statistics was the most common prerequisite, and predictive and descriptive analytics were the most identified topics across programs. They presented an exemplar curriculum for a business analytics minor comprised of three prerequisite courses (basic statistics, 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. They suggested a new minor was not necessary, rather existing IS curriculums could be expanded to include courses focused on business analytics.

Table 2 shows the studies that examined business analytics and data science curricula, and solicited input of industry and academic experts. These studies present primary and secondary data.

4.3 Content Analysis Studies

Real-time labor demand data is useful for understanding the analytics ecosystem. A number of studies have used online analytics job advertisements to identify highly sought-after knowledge and skill sets. At aggregate levels, online job advertisements could be valuable indicators and reveal shifting labor demands as they occur. This could 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 with potential employers. For academics, knowledge of the empirical job-posting data could facilitate the development of KSAs in curricula that expands the number of viable candidates in the applicant pool.

Business intelligence (BI) and big data skills were the focus of Debortoli et al.'s (2014) content analysis of 1,807 Monster.com job advertisements during 2013 and 2014. They created hierarchical, tree-structured taxonomies of the required skills for BI and big data jobs. These taxonomies revealed that for successful initiatives, business skills were as important as 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 with big data. Big data skills were also more analytical and software development oriented.

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 of data analysts (Luo, 2016). 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. Similarly, Cegielski and 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 KSAs 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 et al. (2018) harvested 1,216 job advertisements containing "big data" in the job title from Indeed. Using automatic topic detection and expert verification, 218 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 was also indicated in the analysis of 2,786 job listings scraped from Dice.com during 2015 (De Mauro et al., 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 also ranked highly. Finally, the engineer role was most associated with architecture skills and to a lesser extent cloud, systems management, and distributed computing.

During December 2016 through February 2017, Verma et al. (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 the most frequently mentioned skill set. Organization skills (e.g., teamwork and management) were always found in the top three types of required skills. Statistical skills were conspicuously missing from the business analyst's ideal profile, but it was the data scientist's second most frequently mentioned skill set. Programming skills were 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 et al. (2018) collected 1,050 job postings from 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 offerings. Using both job advertisements (n=8,846) and course descriptions (n=234), they applied clustering analysis to develop a model to predict what courses would be in specific analytic-type programs. The first type of master's program aligned with machine learning and was primarily housed in computer science programs. The second type of program most closely aligned with operations research and was found in business programs.

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 ▪ develop a business analytics professional master's degree
Johnson et al. (2020)	Curriculum analysis	analytics education; business analytics; curriculum design		▪ focus on basic analytic skills (descriptive and predictive analytics) ▪ develop new business analytics master's program ▪ update of UG programs (no specific major mentioned)
UG				
Aasheim et al. (2009)	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	▪ no significant difference between faculty's and IT managers' perceptions of average importance. ▪ update/expand IT/IS UG curricula
Aasheim et al. (2015)	course description content analysis 13 data analytics UG programs	data analytics; job skills; emerging technologies; program improvement	1) data science 2) programs 3) data analytics programs	▪ DS requires more math, statistics, programming ▪ DS requires learning data mining algorithms ▪ DA requires using data mining techniques ▪ data analytics programs as an extension of current IS curricula and data science programs as an extension of current CS curricula
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 ▪ develop new data analytics program (generated from OR, statistics or IS)
Mills et al. (2016)	curriculum review 118 AACSB UG IS programs	big data; data analytics; visualization; business intelligence; model curricula	1) Pillars of Analytics (Kang, Holden, and Yu, 2015)	▪ 60% of AACSB IS programs added data science courses between 2011 & 2016 ▪ expansion/update of IS program
Stephens & McGowan (2018)	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 ▪ develop new BA program (mostly from efforts of MIS or DS faculty)
Burns & Sherman (2019)	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) ▪ update/expand IS curriculum
Ceccucci et al. (2020)	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 ▪ develop new BA program from existing IS program or Update/expand IS program

Table 2. Nonresident Expertise Articles

Johnson et al. (2020) scraped 5,257 business analyst entry-level job postings from Indeed in 2018 and extracted skills, knowledge and tools listed in the job postings. The results were subsequently validated by surveying experts and focus groups. Their results confirmed 1) the need for graduate-level programs, 2) SQL, Python and R were key tools, 3) graduates should have some knowledge of big data platforms, and 4) both analytical and soft skills were required.

Persaud (2021) used Le Deist and 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 was meta-competence, which represented the KSAs needed to address messy, complex challenges. Using text mining on 3,009 job postings for analytics positions from Indeed, LinkedIn, Monster.com, Procom and also the associated academic program materials from 61 Canadian universities and colleges, he identified four broad KSA categories. Technical KSAs, which fell into cognitive and functional competencies, were 1) data analytics and 2) computing. The social and meta-competencies were 3) business and 4) soft skills.

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

Table 3 presents studies that gathered new, original data collected through web scraping and content analysis of online job advertisements.

4.4 Synthesis

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 roles (e.g., 55 jobs titles in Stanton & Stanton, 2020). The most frequently occurring listings were for data scientists, data analysts, and business analysts (e.g., De Mauro et al., 2018; Debortoli et al., 2014; Persaud, 2021; Verma et al., 2019).

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: 1) business, 2) analytics, and 3) technical (e.g., Chang et al., 2019; Chiang et al., 2012; Radovilsky et al., 2018) or hard/soft/software (e.g., Luo, 2016; Stanton & Stanton, 2020). These similarities between the job roles dictate that faculty invest in defining the mission, goals, objectives and scope of their specialized programs. Part of this effort is understanding how one academic unit's offering is different from another. 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 business schools, 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 "data analytics" or "business analytics" as the program name, where computer science schools preferred "data science" as a label (Aasheim et al., 2014, 2015). Business analyst is typically the least technical job role (Verma et al., 2019). 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 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 analysis, 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, 2020). 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., 2019).

Fifth, big data and big data analytics were among 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., De Mauro et al., 2018; Debortoli et al., 2014; Gardiner et al., 2018; Persaud, 2021).

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. Nonresident 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 level of truth in the listed job requirements. In other words, are the real minimum requirements for employment found in the written posting or could the listed requirements be idealized and rarely met?

Two broad research questions emerged from the current narrative review of the existing and emergent literature on the KSAs requirements for data analytics professionals. The first research question was "what competencies do employers require of candidates in data analytics positions?" Within the academic domain, this question is equivalent to asking "what KSAs should our students have at graduation?" The second research question was "what should the relative strengths be among each of those competencies?" Again, within the academic domain, the corresponding questions are "what skills should be developed within a course and given a program's unique identity (identity being formed by the expertise and reputation of the school and faculty)? Additionally, "how advanced should the requirements be for each skill?"

Authors	Scrapping Date Job Title	Major Categories / Concepts	Interesting Points
Debortoli et al. (2014)	2013-2014 BIA, BDA	1) business (domain & management) 2) IT (concepts and methods & products)	▪ BIA skills (more focused on commercial products & vendors) ▪ BDA skills (S/W development, statistical oriented, HR intensive)
Luo (2016)	2013-2014 DA	1) job responsibilities (data mgt, data analysis, insight, project management, functional) 2) 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	1) business 2) analytical 3) technical	▪ validated by a survey of 160 practitioners ▪ indicated priority skills
Gardiner et al. (2018)	2015 Big Data	1) 24 KSA categories 2) 218 skills	▪ 13% of skill terms are soft skills
De Mauro et al. (2018)	2015 BA, DS, developer, engineer	1) 4 job categories 2) 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	1) 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	1) technical 2) analytical 3) business 4) communication	▪ collaborate - the only soft skill in the DS's most frequently mentioned word list
Stanton & Stanton (2020)	2019 DS, DA, BA	1) hard skills 2) soft skills 3) software skills	▪ suggestions: real-world, certifications, when & how to use techniques, coding, soft skills, state-of-the-art tools
Mortenson et al. (2019)		1) type 1 degree – data science / big data 2) type 2 degree – business analytics	▪ type 1- aligned with ML - primarily in comp sci ▪ type 2 closed aligned with OR in business
Johnson et al. (2020)	2018 BA (entry level, not mgmt)	1) tools 2) big data infrastructure 3) technical concepts 4) soft skills	▪ advanced degrees are preferred ▪ SQL, R, and Python are sought after ▪ Inference, sampling and non-sampling errors
Persaud (2021)	2020 BA, DS, DA, data consultant	1) data analytics 2) computing 3) business 4) soft skills	▪ data scientists alone - not sufficient to give companies a real competitive advantage
Seal et al. (2020)	2018-2019 BA	1) soft skills 2) analytic/technical skills	▪ business schools spend too much time on deeply technical topics

Table 3. Job Advertisements – Content Analysis Articles

As Tables 1, 2 and 3 reveal, there are three distinct influencers, sources of ideation and domain expertise: 1) faculty members, 2) industry experts, and 3) the content analyses of job advertisements, which address these two research questions.

Each influencer brings its own strengths and biases. Nonresident industry experts are best positioned to present the archetypes for the data analytics professionals. Industry experts are, ultimately, the stewards of business strategy and best positioned to influence faculty in their decisions concerning curriculum design. In this case, data and analytics skills are the targeted capability. Networking events, advisory councils' meetings, surveys, and Delphi studies are some examples of where and how industry experts and faculty could communicate about the breadth and depth of specific KSAs that are required of candidates. These often routine and recurring interactions provide an ongoing opportunity for both industry input on current KSAs requirements and feedback on how academic programs are meeting those needs, as well as where improvement is indicated.

Alternatively, online job advertisements list the desired capabilities of future hires. The literature clearly delineates between expert opinion and the job advertisement due to the differences in the nature of the insights and the methods for accessing those insights. However, they are not independent.

Industry experts often directly contribute to the hiring process and, specifically, to the content of job advertisements. Thus, little contradiction should exist between the two sources.

Finally, faculty are the stewards of curricula. They, alone, are accountable for the development and delivery of curricula. Although faculty directly determine curricula, their voices should be moderated, in this case, by expert opinions and empirical job advertisements. These influencers are a supplement to faculty's understanding of the fundamental knowledge and skills that are needed to meet employer requirements. Subsequently, by unpacking the input of experts and the content of job advertisements, faculty are better informed to develop curriculum germane to current demands of the job market.

Figure 1, titled "Three Influencers of Data Analytics Curriculum Design," depicts how faculty are informed and influenced by both nonresident expert input and the analysis of actual job advertisements. The fact that a position description is the manifestation of the data analytics professional's expert opinion on candidate requirements is shown by the arrow indicating that the expert (current employee) crafts the job advertisement. Although the insight provided by the expert and the job advertisement are closely linked, they are not the same. Polite conversation with the expert could unduly mask or exacerbate important aspects of a message. Even slight variations in the way a question is worded could lead to miscommunication. For example, an answer to the question "What skills are you looking for in a candidate?" is very different than "What skills would the ideal candidate have?" Both of these questions may yield different answers than "What is the minimum skill level a candidate must have for you to consider hiring that individual?"

The model also adds a temporal perspective on the effects of influencers on curriculum choices by including feedback loops. The actual placement data is a feedback mechanism that validates the effectiveness of curriculum decisions and program performance, as well as a critique of the organization's recruitment efforts. The importance of feedback mechanisms confirms that industry involvement in curriculum development must be an ongoing process, much like strategic planning.

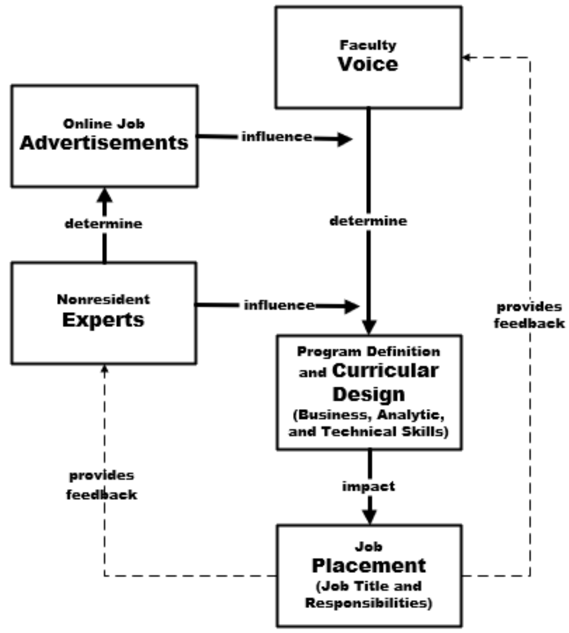

Figure 1. Three Influencers of Data Analytics Curriculum Design

5. POST NARRATIVE REVIEW EXECUTIVE FEEDBACK ON CURRENT FINDINGS

To triangulate the narrative review findings, we asked four nonresident experts (high-level corporate executives with heavy experience in IS) to comment on their companies' preferences for specific educational backgrounds and skills sets in business analytics entry-level position applicants.

When asked if their company hires business analytics personnel, one of the respondents stated that their company did not. This organization adopted a shared-services model where all analytics are outsourced to a number of consulting firms. The respondent did complete the entire exercise sharing their expectations of the skills and backgrounds of high-performing business analysts.

When asked about the responsibilities of the business analyst, the first respondent (R1) described the business analysts as working with the business to understand its strategy and "pain points." According to R1, a business analyst would need to understand the organization's data and tools to access and analyze data to enable the organization to make better decisions faster. The second respondent (R2) described the business analyst role within a framework of required technical skills. R2 talked about specific technologies, artificial intelligence and machine learning. In terms of business impact, R2 said the business analyst would "answer questions as requested." The third respondent (R3) described the business analyst as "working with business users to gather requirements," transforming "information needs into documented data requests" and working with IT to prepare the data so "standard BI tools" can be used "to analyze the data to satisfy business needs." The fourth respondent (R4) described three major functions of the business analyst: 1) working with others to "define an operational framework to ensure precise and secure delivery of knowledge and information," 2) interpretation of statistical results, identification of follow-up actions and communication of results, and 3) coding with 4GL languages and database technologies. When addressing the business analyst role in their own organizations, each respondent emphasized a different area of responsibility. R1 described the business analyst as a strategic partner. R2 described the business analyst role as more passive, responding to requests from the business. It should be noted that the salary range given in our description of the candidate suggests a low level of professional experience. R3 described the business analyst as actively working with the business. R4 focused on analytical and technical skills required for the position.

The respondents were also given a series of seven brief statements describing the backgrounds of potential analytics applicants (see Table 4). They were asked to rank each applicant's suitability for a business analyst position in their company. Two of those options did not involve formal analytics university degrees: 1) a business degree without any specialized analytics options, and 2) the degree is not important as long as the individual had analytics work experience. Two non-business options were 3) a non-business technical degree, such as computer science, engineering or math, 4) a non-business technical degree with a business minor. Two analytics specific undergraduate business options were 5) a business analytics major, and 6) a business analytics minor. The final option was 7) a graduate-level analytics business degree

	RANKINGS (1 most preferred, 5 least preferred)				
RESPONDENT	R1	R2	R3	R4	AVE
UG Business Data Analytics Major	2	2	1	2	1.75
UG Technical (comp-sci, engineering, math) Business Minor	5	1	2	1	2.25
UG Business Data Analytics Minor	3	4	2	4	3.50
Graduate Business Data Analytics	1	5	5	3	3.50
UG Technical (comp-sci, engineering, math)	7	3	4	5	4.75
Degree not important - prior analytics work experience	4	7	7	6	6.00
UG Business	6	6	6	7	6.25

Table 4. Preferred Educational Background

All respondents rated business school analytics options as both their first and second preference. An undergraduate business school degree without an analytics specialty was not ranked favorably. These rankings support the assertion that data analytics is correctly housed in the business school (Aasheim et al., 2014, 2015; Chiang et al., 2012).

R1 ranked the graduate business analytics degree holder as the most desirable candidate and indicated the hypothetical salary range seemed low. Given that contributing to strategy led this respondent's list of responsibilities, it is not surprising that a more credentialled higher paid candidate would be preferred (Chang et al., 2019). When considering only undergraduate options, all four respondents wanted analytics majors for their most preferred candidates. Two respondents indicated that the business school analytics major would be their first choice and the other respondents preferred a technical degree with a business minor. An individual with analytics experience, but no formal university specialization was not viewed favorably.

We also asked the executives to rank the relative importance of each of the three major categories of KSAs: 1) analytical and programming skills, 2) business knowledge and communication skills, and 3) information technology knowledge and skills (Table 5). R1, R2 and R4 selected analytical and programming skills as the most important KSAs. R3 rated analytical and programming skills as the least important.

This small sample of business executives lends support to the results of our narrative review. There was a great deal of agreement among our respondents both with each other and with the literature in terms of desired credentials. Concurrently, the role of business analyst seems to vary across the organizations ranging from 1) a person with analytics skills responding to business questions, 2) to proactively working with business to answer business questions, 3) to partnering with business to identify and address business needs, 4) to acting as an active strategic partner.

	RANKINGS (1 most preferred, 3 least preferred)				
RESPONDENT	R1	R2	R3	R4	AVE
analytical and programming skills	1	1	3	1	1.50
business knowledge and communication skills	2	3	1	2	2.00
information technology knowledge and skills	3	2	2	3	2.50

Table 5. Relative Importance of Skill Sets

6. 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 (content analysis). This effort provides a multi-perspective view of the best practices in the identification of the KSAs needed for different data analytics roles. Furthermore, this study provides insight into the process of developing a new data analytics curriculum.

This narrative review also led to the creation of a new model – *Three Influencers of Data Analytics Curriculum Design*. This model highlights how all three influencers (faculty voice, non-resident experts, online job advertisements) work together in a framework for curriculum development. The interactive nature of the relationships among the influencers provides natural feedback mechanisms for continual improvement. Ongoing interaction between faculty and the business community is a key tenant of this model. With this knowledge, business school faculty would be better informed to develop distinctive programs that capitalize on their unique strengths and keep those programs current while simultaneously meeting or exceeding the expectations of their students.

Our findings also highlight the importance of advisory committees that serve as a bridge between the business community and faculty. They could assist faculty members in understanding and responding to industry needs. Advisory committees could advise and validate curriculum design so that the program could meet the needs of the community it serves. Ongoing interaction with industry experts in advisory committees becomes especially important in a field such as data analytics that grows and changes rapidly, and curriculum change should respond quickly enough to meet employer needs.

A limitation of this type of study is the difficulty matching specific low-level skill descriptions to higher-level course topics. Further investigation is needed to better understand the relative importance of specific skills in securing employment and enhancing job performance. More multi-method studies are necessary to understand any biases in the reported prerequisite skills. For example, if employers were to describe the skill levels they want in candidates, would they settle for lesser skills because of a perceived lack of skills among the candidate pool? This type of information is necessary, not only for faculty to make better curriculum choices and decisions about the percentage of class time dedicated to specific topics, but this information would also be helpful in developing a data analytics model curriculum. Therefore, it is imperative that faculty maintain ties with industry experts and continue the analysis of data analytics job advertisements so students are well-prepared to meet industry needs.

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