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Data Science, Predictive Analytics, and Big Data in Supply Chain Management: Current State and Future Potential

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While data science, predictive analytics, and big data have been frequently used buzzwords, rigorous academic investigations into these areas are just emerging. In this forward thinking article, we discuss the results of a recent large-scale survey on these topics among supply chain management (SCM) professionals, complemented with our experiences in developing, implementing, and administering one of the first master's degree programs in predictive analytics. As such, we effectively provide an assessment of the current state of the field via a large-scale survey, and offer insight into its future potential via the discussion of how a research university is training next-generation data scientists. Specifically, we report on the current use of predictive analytics in SCM and the underlying motivations, as well as perceived benefits and barriers. In addition, we highlight skills desired for successful data scientists, and provide illustrations of how predictive analytics can be implemented in the curriculum. Relying on one of the largest data sets of predictive analytics users in SCM collected to date and our experiences with one of the first master's degree programs in predictive analytics, it is our intent to provide a timely assessment of the field, illustrate its future potential, and motivate additional research and pedagogical advancements in this domain.

Keywords: data science; predictive analytics; big data; data scientist; supply chain management; education; curriculum development

INTRODUCTION

A topic that is on the minds of many supply chain management (SCM) professionals is how to deal with massive amounts of data, and how to leverage and apply predictive analytics. This challenge is a direct result of the ease with which data have been able to be collected via modern information technology, generating unprecedented volume, variety, and velocity of data. Heralded to revolutionize how SCM is conducted (Waller and Fawcett 2013b), predictive analytics has the potential for significant above-average returns (McAfee et al. 2012). Within the context of SCM, predictive analytics can be defined as using "both quantitative and qualitative methods to improve supply chain design and competitiveness" (Waller and Fawcett 2013b, 80). Predictive analytics is positioned within the overall domain of data science, which refers to "the application of quantitative and qualitative methods from a variety of disciplines in combination with SCM theory to solve relevant SCM problems and predict outcomes, taking into account data quality and availability issues" (Waller and Fawcett 2013b, 79).

Despite the importance and relevance of SCM predictive analytics, "there is a dearth of literature on the topic and many questions" (Waller and Fawcett 2013b, 77). While articles in practitioner outlets and consultancy reports are becoming more prevalent, their content is mostly repetitive, and rigorous scientific investigations into the topic have been absent. In addition, while companies are experimenting with "big data analytics," for the majority, its application has been elusive or has only scratched the surface of what may be possible. The need for well-trained data scientists is thus imminent (Dwoskin 2014). Further research into predictive analytics is also needed, both from an academic and a practical perspective. It is the objective of this forward thinking article to contribute to this domain, and provide an assessment of its current state and future potential. We specifically aim to answer the following questions: (1) What is the current extent of use of SCM predictive analytics, and what are the underlying motivations? (2) What are benefits and barriers to SCM predictive analytics? and (3) How can we train our next-generation data scientists?

We rely on two primary data sources to develop our insights. The first consists of a large-scale survey of 531 SCM professionals (administered in September 2013), inquiring about their current use, associated motivations, benefits and barriers to data science, predictive analytics, and big data, as well as desired skill sets. With this data set, we provide an assessment of the domain's current state. The second data source is comprised of insight derived from developing, implementing, and administering one of the first predictive analytics' master's degree programs at a major U.S. research university. Specific data sources consulted for the development of this article include workshops, company interviews, and student feedback (both pre- and post-graduation). With these data, we are able to assess the domain's future potential, offering insight into how next-generation data scientists are trained. This exposition should be especially useful to those institutions that are contemplating the development of their own degree programs in predictive analytics. Our discussion of the development and modifications over the last three years, including lessons learned, should offer further invaluable guidance for these institutions; it essentially represents a blueprint or template for such a program.

SCM PREDICTIVE ANALYTICS

Extent of use and motivation

To obtain insight into the current state of SCM predictive analytics adoption, we conducted a large-scale survey among SCM

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professionals. A total of 531 individuals responded to the online survey. As a requirement for participation, respondents had to be in a function commonly associated with SCM (logistics/transportation, operations management, SCM, purchasing/procurement/sourcing, engineering, or research and development). We asked respondents to indicate their current use of analytics in terms of whether (1) they currently do not use analytics but plan to do so in the future, (2) they use analytics to some extent, (3) they use analytics to a great extent, (4) they currently do not use analytics and also do not have any plans to use it in the future, or (5) they are not familiar with analytics. Table 1 presents the results.

Most respondents were in logistics/transportation (45.2%), followed by operations management (20.9%), and SCM (17.9%). About half of the sample indicated using predictive analytics to some (27.7%) or to a great extent (13.2%), or plans to use it in the future (8.7%). The other half of the sample was either not familiar with predictive analytics (28.4%) or they did not have any plans to use it in the future (22.0%).

The results offer intriguing insight into the current and planned adoption of SCM predictive analytics. Encouraging is the fact that more than 40% of the respondents actively use analytics. However, while some of the remaining sample plan to use the approach in the future (8.7%), many respondents do not plan to go this route (22.0%). It was also surprising that about one-third of the respondents were not familiar with analytics (28.4%), especially in light of a survey conducted two years prior, which reported only 7% not being familiar with data analytics (Russom 2011). This illustrates the significant educational work that still has to be conducted in introducing these individuals to predictive analytics' potential.

As our focus was on the use of SCM predictive analytics, we disqualified all respondents who were not familiar with analytics or who did not have any plans for its future use. We further removed all data with missing values. This yielded a total of 212 complete and useable records, which are used for the subsequent analyses.

One of our objectives was to identify the motivations for using predictive analytics. To tap into this domain, respondents were provided with a list of potential motivators, to which they were asked to indicate the extent that these motivate/influence their use of such approaches for SCM. The scale was anchored at "not at all" (value = 1) and "to a great extent" (value = 7). The list of motivators was derived from an extensive literature review of primarily practitioner articles on this topic and interaction with SCM professionals.

Table 2 presents the results, also split by usage group (there were no significant differences when contrasting the three usage groups based on the respondent's function). Looking at the overall mean, encouragement by senior leadership and the respondent's conviction about the value of SCM predictive analytics were the most prominent motivators, followed by internal colleagues, competitors, and customers using analytics. Coverage in the popular press did not seem to influence the respondents' motivation.

Intriguing are the results based on the comparison by usage group, which was accomplished by means of analyses of variance (ANOVAs). Most significant differences across the three

Table 1: Cross-tabulation of function and usage group

	Usage group					
Function	**No current use, but plans for the future**	**To some extent**	**To a great extent**	**No current use, no plans for the future**	**Not familiar with data analytics**	**Total**
Logistics/transportation (count)	19	66	23	55	77	240
% Within function	7.9	27.5	9.6	22.9	32.1	100.0
% Within usage group	41.3	44.9	32.9	47.0	51.0	45.2
Operations management (count)	10	27	9	32	33	111
% Within function	9.0	24.3	8.1	28.8	29.7	100.0
% Within usage group	21.7	18.4	12.9	27.4	21.9	20.9
Supply chain management (count)	8	29	26	13	19	95
% Within function	8.4	30.5	27.4	13.7	20.0	100.0
% Within usage group	17.4	19.7	37.1	11.1	12.6	17.9
Purchasing/procurement/sourcing (count)	6	9	6	2	10	33
% Within function	18.2	27.3	18.2	6.1	30.3	100.0
% Within usage group	13.0	6.1	8.6	1.7	6.6	6.2
Engineering (count)	2	5	3	10	7	27
% Within function	7.4	18.5	11.1	37.0	25.9	100.0
% Within usage group	4.3	3.4	4.3	8.5	4.6	5.1
Research & development (count)	1	11	3	5	5	25
% Within function	4.0	44.0	12.0	20.0	20.0	100.0
% Within usage group	2.2	7.5	4.3	4.3	3.3	4.7
Total (count)	46	147	70	117	151	531
% of total	8.7	27.7	13.2	22.0	28.4	100.0

Table 2: Motivation to use SCM predictive analytics

		Usage group			
Motivation	**Overall mean**	**No current use, but plans for the future (1)**	**To some extent (2)**	**To a great extent (3)**	**ANOVA F-value and sign.**
My conviction	4.73 (1.36)	$4.17^{(3)}$ (1.36)	$4.55^{(3)}$ (1.25)	$5.40^{(1,2)}$ (1.33)	12.62**
Internal colleagues	4.47 (1.48)	$3.94^{(3)}$ (1.55)	4.44 (1.39)	$4.83^{(1)}$ (1.54)	4.20*
Customers	4.11 (1.73)	4.11 (1.69)	$3.84^{(3)}$ (1.70)	$4.62^{(2)}$ (1.72)	4.06*
Competitors	4.25 (1.77)	4.19 (1.58)	$4.03^{(3)}$ (1.80)	$4.72^{(2)}$ (1.75)	3.11*
Encouragement by senior leadership	4.78 (1.57)	4.42 (1.52)	4.72 (1.58)	5.12 (1.54)	2.47*
Suppliers	4.05 (1.70)	4.03 (1.50)	3.97 (1.75)	4.22 (1.73)	0.43
Press coverage	3.06 (1.65)	3.25 (1.56)	3.00 (1.67)	3.07 (1.67)	0.32

Notes: This table shows means and standard errors (in parentheses). The numbers in the superscripted parentheses indicate the group score number from which the group score is significantly different. Due to unequal sample sizes, *post hoc* pairwise comparison tests were conducted utilizing the Hochberg test statistic. $^{**}p < .001$, $^{*}p < .05$.

groups existed on the individual's conviction serving as a motivator. The valuable implication derived from this finding is that an SCM professional's conviction about the value of SCM predictive analytics is one of the primary drivers for early adoption. The result may also be indicative of users realizing the value of the approaches once they are actively being utilized, further increasing the individual's conviction. To a lesser degree, internal colleagues, customers, and competitors serve as distinguishing characteristics being related to more frequent use of predictive analytics. Two further statements, while serving as a motivator for all, did not differentiate across the three groups (encouragement by senior leadership and suppliers).

Benefits and barriers

A further primary objective of this research was to identify benefits of and barriers to SCM predictive analytics. Similar as above, respondents were provided with a list of potential benefits and

Table 3: Benefits of the use SCM predictive analytics

		Usage group			
Benefits	**Overall mean**	**No current use, but plans for the future (1)**	**To some extent (2)**	**To a great extent (3)**	**ANOVA F-value and sign.**
Better/more informed decision making	5.57 (1.23)	$5.36^{(3)}$ (1.44)	$5.40^{(3)}$ (1.18)	$6.03^{(1,2)}$ (1.09)	6.21**
Increased visibility	5.22 (1.36)	5.14 (1.29)	$5.01^{(3)}$ (1.42)	$5.68^{(2)}$ (1.17)	5.17**
Better management of supply chain risk	5.13 (1.33)	4.97 (1.21)	$4.94^{(3)}$ (1.38)	$5.58^{(2)}$ (1.21)	5.11**
Improvement in supply chain costs	5.26 (1.44)	5.19 (1.28)	$5.03^{(3)}$ (1.51)	$5.73^{(2)}$ (1.26)	4.91**
Enhanced bargaining position in negotiations with suppliers	4.62 (1.60)	4.50 (1.63)	$4.38^{(3)}$ (1.60)	$5.15^{(2)}$ (1.46)	4.90**
Improvement in supply chain efficiencies	5.32 (1.32)	5.28 (1.23)	$5.12^{(3)}$ (1.34)	$5.72^{(2)}$ (1.28)	4.15*
Enhanced demand planning capabilities	5.28 (1.29)	5.06 (1.33)	5.17 (1.29)	5.63 (1.21)	3.29*
Enhanced sales and operations planning (S&OP) capabilities	4.97 (1.33)	4.69 (1.26)	4.88 (1.31)	5.32 (1.37)	3.14*
Enhanced bargaining position in negotiations with customers	4.56 (1.59)	4.31 (1.58)	4.41 (1.60)	4.98 (1.52)	3.12*
Ability to respond faster to changing environments	5.11 (1.30)	4.86 (1.48)	5.03 (1.27)	5.43 (1.18)	2.82*
Real-time decision-making capability	5.12 (1.31)	5.06 (1.29)	4.97 (1.34)	5.45 (1.23)	2.80*
Greater power in relationships with suppliers	4.73 (1.52)	4.72 (1.52)	4.58 (1.54)	5.03 (1.45)	1.80
Greater power in relationships with customers	4.83 (1.55)	4.75 (1.59)	4.72 (1.58)	5.10 (1.46)	1.28

Notes: This table shows means and standard errors (in parentheses). The numbers in the superscripted parentheses indicate the group score number from which the group score is significantly different. Due to unequal sample sizes, *post hoc* pairwise comparison tests were conducted utilizing the Hochberg test statistic. $^{**}p < .01$, $^{*}p < .05$.

barriers, as identified by the authors via primarily practitioner articles and interaction with SCM professionals. The same 7-point scale as above was used, and similar group comparisons based on ANOVAs were conducted.

The results for the benefits are presented in Table 3, which also includes a split by usage group (ANOVAs based on the function again did not yield significant differences between the groups). Benefits were especially seen in the form of more informed decision-making capabilities, ability to improve supply chain efficiencies, enhanced demand planning capabilities, improvement in supply chain costs, and increased visibility.

Significant differences existed between the three usage groups for at least six of the perceived benefits. In general, the "super users" (i.e., those using analytics to a great extent) were much more convinced about the benefits pertaining to better decision making, increased visibility, better risk management, improvement in SCM costs, the creation of an enhanced bargaining position with suppliers, and improvement in supply chain efficiencies. The implication of these findings is that with increased use of predictive analytics, the magnitudes with which these benefits are perceived increases. These benefits, which are anticipated by all three groups, thus seem to materialize in even greater magnitude once predictive analytics are used to some or to a great extent. This result may be indicative of expectations pertaining to these benefits being surpassed with the actual use of predictive analytics. For the remaining benefits statements, in general, the extent to which the benefits were perceived increased nominally when moving from the group that has plans for the future use, to the group that uses predictive analytics to some extent, and to the group that uses predictive analytics to a great extent. However, ANOVA F-statistics indicated that these differences were not statistically significant. All postulated benefits were however perceived as being favorable, as indicated by the mean values being above the midpoint of the scale.

Table 4 offers the results for the barriers to SCM predictive analytics, again also split by usage group (ANOVAs based on the function again did not yield significant differences between the groups). Primary barriers as perceived by our respondents include employees being inexperienced (and the need for training), time constraints, lack of integration with current systems, the costs of currently available solutions, change management issues, lack of appropriate predictive analytics solutions for SCM, as well as the perception of SCM predictive analytics being overwhelming and difficult to manage.

Significant differences between the three usage groups existed only for two barriers identified, that is, lack of data, and the inability to identify data most suitable for predictive analytics. Both of these barriers were perceived to be more severe by the group that plans to use analytics in the future, compared to the group that already uses analytics to a great extent. Efforts thus need to be undertaken by the former group to identify appropri-

Table 4: Barriers to the use SCM predictive analytics

		Usage group			
Barrier	**Overall mean**	**No current use, but plans for the future (1)**	**To some extent (2)**	**To a great extent (3)**	**ANOVA *F*-value and sign.**
Lack of data	3.83 (1.50)	4.42$^{(3)}$ (1.32)	3.79 (1.35)	3.55$^{(1)}$ (1.79)	3.93*
Inability to identify most suitable data	3.99 (1.48)	4.50$^{(3)}$ (1.56)	4.00 (1.41)	3.67$^{(1)}$ (1.50)	3.66*
Security concerns	3.84 (1.71)	4.36 (1.69)	3.86 (1.69)	3.50 (1.71)	2.91*
Lack of upper management support	3.83 (1.74)	4.39 (1.40)	3.83 (1.79)	3.52 (1.78)	2.87*
Unclear business case or value	3.83 (1.44)	4.19 (1.04)	3.89 (1.41)	3.52 (1.65)	2.77*
Privacy/confidentiality issues	3.80 (1.72)	4.28 (1.60)	3.84 (1.70)	3.45 (1.77)	2.71*
Lack of policies and governance structure	3.91 (1.57)	4.14 (1.31)	4.03 (1.59)	3.53 (1.65)	2.54*
Inability to make sense of available data	3.95 (1.54)	4.39 (1.48)	3.96 (1.44)	3.67 (1.71)	2.51*
No need/not necessary/no benefit	3.30 (1.64)	3.67 (1.45)	3.34 (1.60)	2.98 (1.80)	2.07
Overwhelming, difficult to manage	4.16 (1.46)	4.56 (1.46)	4.15 (1.33)	3.95 (1.66)	1.97
Cost of currently available solutions	4.48 (1.48)	4.86 (1.44)	4.41 (1.38)	4.38 (1.68)	1.44
Lack of integration with current systems	4.61 (1.51)	4.92 (1.50)	4.62 (1.45)	4.40 (1.60)	1.33
Employees are inexperienced (need to train)	4.92 (1.47)	4.92 (1.61)	4.83 (1.47)	5.12 (1.38)	0.77
Change management issues (resistance to change)	4.44 (1.64)	4.56 (1.61)	4.32 (1.67)	4.60 (1.59)	0.69
Lack of appropriate solutions for SCM	4.33 (1.41)	4.56 (1.46)	4.30 (1.33)	4.25 (1.54)	0.58
Current applications unable to meet business needs	3.96 (1.49)	4.14 (1.40)	3.87 (1.44)	4.03 (1.64)	0.54
Time constraints	4.63 (1.37)	4.56 (1.56)	4.71 (1.25)	4.52 (1.49)	0.44

Notes: This table shows means and standard errors (in parentheses). The numbers in the superscripted parentheses indicate the group score number from which the group score is significantly different. Due to unequal sample sizes, *post hoc* pairwise comparison tests were conducted utilizing the Hochberg test statistic. *$p < .05$.

ate data. Most likely, some type of data exist that may be suitable for predictive analytics, due to the ease with which data can be collected today—it just needs to be identified, made palatable, and worked with. It may also just need an illustration how existing data can be readily used for predictive analytics—the data may be there, but individuals may not realize its suitability. For the remaining barriers, a similar pattern is evident, although not significant at statistically detectable levels.

Table 5: Skill sets required for data scientists

	Mean	SD
Understanding application of qualitative and quantitative methods of forecasting	5.38	1.216
Numerical methods of optimization	5.19	1.117
Broad awareness of many different methods of estimation and sampling	5.18	1.113
Determining opportunity cost	5.17	1.224
Using numerical methods to estimate functions relating independent variables to dependent variables	5.08	1.137
Using probability theory with actual data to estimate the expected value of random variables of interest	5.04	1.196
Quick design and implementation of discrete event simulation models	4.92	1.248
Capital budgeting	4.88	1.269
Managerial accounting	4.74	1.275
Marketing science	4.67	1.221

Positioning our findings within the literature

Academic research into data science, predictive analytics, and big data in SCM has been scarce. The few papers that exist introduced and defined the domain, and called for further research (Waller and Fawcett 2013a,b), stressed the importance of data quality (Hazen et al. 2014), and tested the relationship between big data analytics and operational performance (Chae et al. 2014). It has been noted that big data analytics facilitates enhanced decision making, increased visibility, better risk management, and overall greater value (Akkermans and Van Wassenhove 2013; Lycett 2013; Chae et al. 2014). However, we were not able to find academic research that addressed the current extent of use, motivations, benefits, and barriers to predictive analytics. It is in these areas where our contributions lie.

Focused case studies and surveys of predictive analytics in SCM have been published in practitioner journals and consultancy white papers. For example, Russom (2011) provided a first look into the adoption of big data analytics, Cecere (2012a) offered insight into firms' capabilities to use big data sources and how to get started with data analysis, and Cecere (2012b) identified big data supply chains as an exciting trend among her respondents. Manyika et al. (2011) positioned big data as the next frontier for innovation, competition, and productivity, and Balboni et al. (2013) identified levers for companies to successfully pursue data analytics. In addition, LaValle et al. (2011) drew attention to managerial and cultural obstacles to the adoption of big data analytics, and Jaspersoft (2014) found increasing commitment to big data projects. While the insights provided by these studies are valuable, our work builds upon these prior findings by obtaining a significantly larger number of respondents, and by providing more detail in our analysis. Our results and

Table 6: Expert interviews on desired skill sets

Expert and title	Company	Desired skill sets
Tim Rey, Director of Advanced Analytics	Steelcase	Being able to convert data into business gain; being inquisitive about problems; creativity, having a mathematical slant; statistics; machine learning; operations research
Philip Lear, Manager of Trade Analytics	Kellogg's	Critical thinking; mathematics; programming; however, it is not really only about crunching numbers and getting statistics, but to develop insights from numbers; understanding the business behind it is thus important; passion
David Dorleans, Manager, Advanced Risk and Compliance Analytics	PriceWaterhouseCoopers	Ability to analyze the data, but then also to convey useable results and implications to executives (communication skills)
Mike Marshall, Director of Marketing and Statistical Science	J.D. Power & Associates	Quantitative skill sets, ability to find and see patterns, passion for discovering things; inquisitive mindset; technical capabilities and skill sets
Richard Rodts, Manager of Global Academic Programs for Data Analytics	IBM	Understanding what questions to ask (not necessarily with a big technology background); being able to address business needs; leverage technology to look further into data to facilitate better decisions; communication skills (need to tell a story about why the data matter); mathematics; sociology
Jeremie Juban, Chief Data Scientist, Statistics, Data Mining, Machine Learning	The Weather Company	Being able to spend time with the data, coupled with the desire to understand what is behind the data

Source: https://accounting.broad.msu.edu/welcome/ms-business-analytics/events/

analysis therefore not only make valuable contributions to academic research, but also to the practitioner press.

TRAINING NEXT-GENERATION DATA SCIENTISTS

Educating scientists capable of mastering the challenges of predictive analytics is of utmost importance. This was highlighted in a report by McKinsey & Company (Manyika et al. 2011, 3), which estimated "a shortage of 140,000 to 190,000 people with deep analytical skills as well as 1.5 million managers and analysts to analyze big data and make decisions based on their findings" by 2018. This lack of trained talent thus represents a major obstacle for realizing the full potential of SCM predictive analytics. In the following sections, we aim to contribute to efforts targeted at reducing this challenge. We commence with an exposé of desired skill sets for data scientists, as identified in our survey. We then continue with a description of the design and implementation of a Master of Science (MS) degree program in predictive analytics at a major U.S. research university, as well as efforts currently under way to bring the domain of predictive analytics closer to our undergraduate population.

Skill sets for data scientists

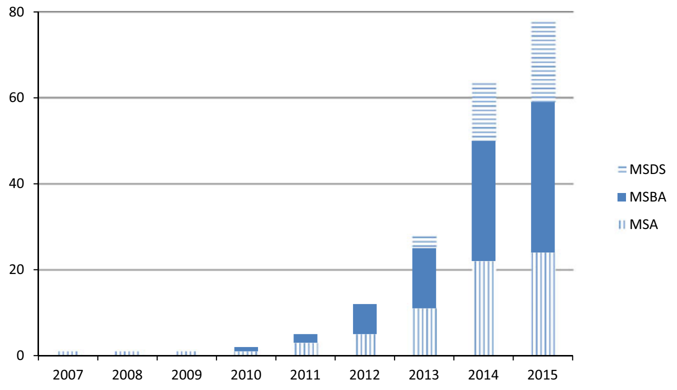
While a data-scientific skill set and knowledge are crucial for supply chain leaders (Waller and Fawcett 2013b), limited insight exists on what these skill sets should entail. Waller and Fawcett (2013b) conjectured about SCM data scientist skill sets that seem to be more important. However, unable to confirm them, the authors called for research to "address which skill sets are needed by SCM data scientists" (Waller and Fawcett 2013b, 79). We directly follow this call in this forward thinking article. Specifically, we took the aspects that were deemed to be more important for an SCM data scientist's skill set summarized in their table 1 (Waller and Fawcett 2013b, 79), and asked our respondents to indicate on a 7-point scale whether they feel the particular skill is "not needed at all" (value = 1) or "definitely needed" (value = 7). Table 5 presents the results.

The skills needed most, as suggested by our respondents, come from the disciplines of forecasting (qualitative and quantitative), optimization, statistics (methods of estimation and sampling), and economics (determining opportunity cost). Mathematical modeling and applied probability are also high on the list. Skill sets still required, but deemed to be of lesser importance, come from the disciplines of marketing, accounting, and finance, which have been viewed as more general domains and, on average, less quantitative, at least as compared to disciplines such as optimization and statistics. Contrasting the evaluation of the skill sets across our three usage groups and across the functions yielded only nonsignificant differences.

We complement the insight derived by the survey with expert interviews from companies promoting the use of predictive analytics. Table 6 summarizes the results of these interviews, suggesting additional skill sets required. Two key themes emanate from these comments: data manipulation and communication/interpersonal skills. With respect to data manipulation, data scientists must have the skills to extract transactional data from databases and data warehouses, scrape social media sites like Facebook, and transform the data by integrating internal and external data together into a single repository. Such skills require database and data manipulation knowledge, both of structured and unstructured data.

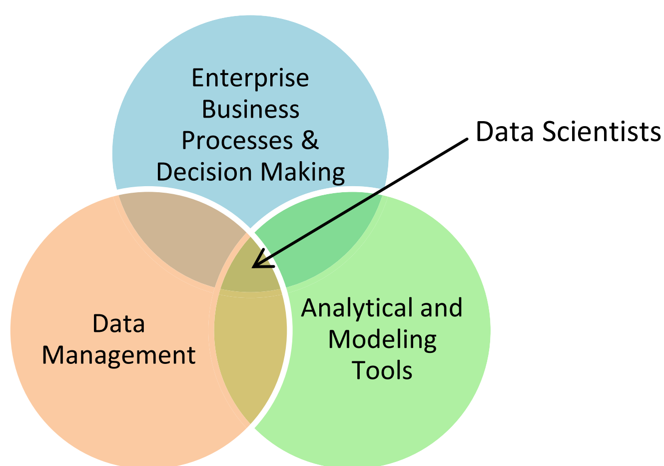
In addition, many interviewees emphasized the need for strong communication and interpersonal skills. The implication is that data scientists not only need to handle data very well, but they also need to possess the capability to communicate the insights derived in an effective way. The experts further noted that the identification and development of appropriate skill sets is still work in progress. For example, Richard Rodts, Manager of Global Academic Programs for Data Analytics at IBM, noted that the position of the modern data analyst did not exist until the very recent past. In addition, as Philip Lear, Manager of Trade Analytics at Kellogg's, suggests, predictive analytics have evolved from a somewhat obscure topic five years ago, to something that everyone today wants.

Figure 1: Growth in MS Analytics programs in the United States based on initial year of program launch. MSA, Master of Science in Analytics; MSBA, Master of Science in Business Analytics; MSDS, Master of Science in Data Science.



Source: North Carolina State University (2014).

Figure 2: Skill sets for data scientists.



A MS in predictive analytics

Waller and Fawcett (2013a) encouraged the provision of a curriculum to train next-generation graduates to successfully tackle the challenges of data science. We directly follow their call by providing a description on how a large U.S. university trains their next-generation data scientists. In this section, we first provide some perspective on the growth of MS in Analytics programs, and then focus on the development and initiation of the MS in Predictive Analytics at this institution. The ensuing section then describes the efforts that are currently being conducted at the undergraduate level.

A number of universities have and/or are in the process of implementing new curricula to serve the growing demand for

Table 7: MS programs in analytics

University	Credits	Time commitment	Year established	Program length	Business processes and decision making (%)	Data management (%)	Analytical and modeling tools (%)	Integration (%)
Arizona State University	30	FT/O	2013	9–16 months	18	27	46	9
Carnegie Mellon University*	–	FT	2013	12–21 months	36	23	25	16
DePaul University	52	O	2010	24 months	–	43	43	14
Drexel University*	45	PT/O	2012	20 months	22	34	33	11
Fordham University*	30	FT	2012	12 months	29	42	29	–
Louisiana State University	39	FT	2011	12 months	5	30	52	13
Michgian State University	30	FT	2013	12 months	13	20	47	20
New York University	36	FT/PT	2013	15–21 months	33	20	40	7
North Carolina State University	30	FT	2007	10 months	15	25	45	15
Northwestern University*	–	O	2011	20 months	10	10	70	10
Northwestern University	–	FT	2012	15 months	20	27	33	20
Rensselaer Polytechnic Institute*	30	FT	2013	12 months	16	34	34	16
Rutgers University*	43	FT/PT	2012	12–21 months	30	20	40	10
Southern Methodist University*	33	FT	2013	18–24 months	46	8	46	–
University of Cincinnati*	25	FT/PT	2011	12–20 months	–	8	76	16
University of Tennessee*	39	FT	2010	17 months	22	10	58	10
University of Connecticut*	33	FT/PT	2012	12+ months	44	28	28	–
University of Maryland	30	FT	2013	9 months	48	10	36	6
University of San Francisco	35	FT	2012	11 months	15	20	54	11
University of Texas*	36	FT	2013	12 months	13	25	50	12

Notes: *The percentage mix reflects required courses; elective course selections would change the actual percentage allocations. FT, Full time, on campus program; PT, Part time, on campus program; O, Online program.

data science capabilities. At one end of the spectrum this curriculum involves certificate and executive education programs to expose participants to core concepts in data science. At the other end of the spectrum are well-developed and robust curricula leading to a master's or undergraduate degrees in data science.[1] As illustrated in Figure 1 (North Carolina State University 2014), there has been tremendous growth in the number of MS Analytics programs with a significant uptick in the number of programs in 2014 and 2015.

One of the most challenging curricular aspects of developing sufficient applicable skills in data science is the breadth and depth of diverse skill sets that are needed to be a highly capable professional. Furthermore, individuals who may have an interest in one dimension associated with data science are unlikely to have developed skills or even been exposed to conceptual foundations and skills in another area. Thus, a data scientist must develop deep conceptual understanding and applicable skills in three areas—enterprise business processes and decision making, data management, and analytical and modeling tools (Figure 2). Given the disparate nature of these areas, it is critical that the development process includes experiential learning to provide the necessary practice of integrating these areas and understanding how to master the skills in specific domains.

We conducted an analysis of MS in Analytics programs that were established in 2013 or prior, and which have received recognition as a "top" program (BISoftwareInsight 2014; MastersInDataScience 2014). We excluded programs that focused strictly on concentrations in existing MBA programs to examine differences among the specific MS curricula. As can be seen in the summary provided in Table 7, there is tremendous variation in these programs—credit hours vary substantially, but a majority of the programs identified require between 30 and 39 credits, with some programs requiring considerably more. Consistent with the number of credit hours, a majority of these programs support degree completion in one year or less. Those requiring substantially more time are often designed as online or part-time programs, and typically target working students who cannot attend a full-time program.

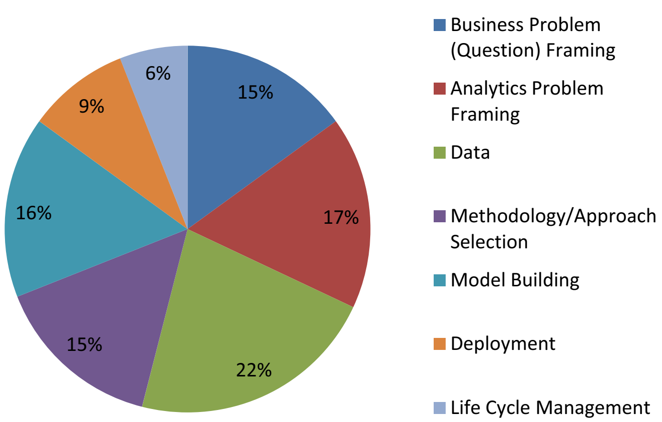
Perhaps, the most interesting variation can be seen across the three knowledge/skill domains previously described (enterprise business processes and decision making, analytical and modeling tools, data management), being indicative of the different programmatic foci of the offerings.[2] Stressing our conviction about the value of practical application of course content, we added an "integration" category to reflect the number of programs that included formal "hands-on" projects enabling students to gain critical expertise in linking these disparate areas of knowledge together.

As can be seen in Table 7, almost all programs have some split of content across these three core areas, with the general emphasis being on analytical and modeling tools (44% on average), followed by business processes and decision making (24% on average), and data management (23% on average). This stresses the importance of not only the proficiency in tools and approaches but also how to make use of the derived data and develop actionable insight and recommendations. A particular emphasis in one area can be explained by where the program's department is housed or where the program originated. In addition, all but two programs have designed integrative coursework into their required courses, highlighting the recognition of the beneficial learning outcomes of this approach.

To provide the foundation for the three skill set areas and put them into perspective, we highlight the analytics certificate program developed within the Institute for Operations Research and the Management Sciences (INFORMS) designed to "enable analytics professionals (and their employers) to have confidence that a person will bring a core set of analytics skills to a project team" (Nestler et al. 2012, 26). The INFORMS certification involves proficiency in seven domains where some domains receive greater emphasis than others as illustrated in Figure 3 (INFORMS 2014). The certification domains are consistent with the primary foci of many existing university programs. To illustrate the overlap with the three skill set areas identified above, we highlight the job tasks identified by INFORMS accordingly (see Figure 4). This aggregation of domains and the ensuing framework presented the foundation for the curriculum development for the MS degree program in predictive analytics at our institution, which we further describe in the following.

The university designed and implemented an MS in Predictive Analytics program that commenced with the Spring 2013 term. The one-year program, split into three semesters (spring, summer, fall), is designed to enhance a professional's existing quantitative background with deep and focused skill development in

Figure 3: INFORMS certification curricular focus.



Source: INFORMS (2014).

[1]The title associated with the degree varies by institution and includes data science, business analytics, predictive analytics, data analytics, etc.

[2]Our assessment of the programs was based strictly on the required courses (elective courses could be taken across the three domains and, as such, could not be meaningfully included in the total allocations). Further, the course description for each program was reviewed on all of the university websites. While it was straightforward to identify the core focus for most courses, there were a number of courses that straddled two of the knowledge domains. In these cases, the researchers assessed, based on course title and content description, which of the domains appeared to be the primary focus.

the three principal areas identified above: enterprise business processes and decision making; data management; and analytical and modeling tools.

Experiential learning, embedded in each of the three semesters the students are enrolled, involves an integration of the three foundational areas by performing a corporate analytics project in partnership within an organization. Participating companies have included Fortune 500 and medium-sized businesses in the insurance, automotive, financial services, energy, and manufacturing industries as well as governmental entities. While many of the projects involve customer-facing applications creating predictive models regarding customer churn and customer lifetime value, there is increasing interest in financial, cost management, supply chain (e.g., predicting logistics and quality failures), and human resource (e.g., employee churn) applications. The analytical tools applied have ranged from traditional statistics to sophisticated predictive modeling applications (e.g., SPSS Modeler) and programming in R to develop customized statistical and visual analyses.

The current curriculum for the MS program is presented in Figure 5, with Figure 6 illustrating its evolution. As noted in Figure 5, the 30 credits of content associated with the MS program cut across all three of the core foundations, and are highly experiential and integrative. We have found that developing depth of knowledge in business processes and decision making is critical, yet is most impactful when developed within the context of a specific analytics problem.

While the content of the program is highly consistent with the job task skills presented in Figure 4, there are several observations to share as we begin our third year of delivering this program, which is scheduled to commence with the Spring 2015 term. First, we cannot overstate the importance of developing communication skills and the use of visualization in presenting analytic findings to business managers. While we have only a single course focused on developing and practicing this skill formally, students practice and enhance their presentation of findings and actionable recommendations in the experiential learning projects and in almost every course.

Figure 4: INFORMS job tasks associated with each domain.

Domain I	**Business Problem (Question) Framing**
T-1	Obtain or receive problem statement and usability requirements
T-2	Identify stakeholders
T-3	Determine if the problem is amenable to an analytics solution
T-4	Refine the problem statement and delineate constraints
T-5	Define an initial set of business benefits
T-6	Obtain stakeholder agreement on the problem statement
Domain II	**Analytics Problem Framing**
T-1	Reformulate the problem statement as an analytics problem
T-2	Develop a proposed set of drivers and relationships to outputs
T-3	State the set of assumptions related to the problem
T-4	Define key metrics of success
T-5	Obtain stakeholder agreement
Domain III	**Data**
T-1	Identify and prioritize data needs and sources
T-2	Acquire data
T-3	Harmonize, rescale, clean, and share data
T-4	Identify relationships in the data
T-5	Document and report findings (e.g., insights, results, business performance)
T-6	Refine the business and analytics problem statements
Domain IV	**Methodology (Approach) Selection**
T-1	Identify available problem solving approaches (methods)
T-2	Select software tools
T-3	Test approaches (methods)
T-4	Select approaches (methods)
Domain V	**Model Building**
T-1	Identify model structures
T-2	Run and evaluate the models
T-3	Calibrate models and data
T-4	Integrate the models
T-5	Document and communicate findings (including assumptions, limitations, and constraints)
Domain VI	**Deployment**
T-1	Perform business validation of the model
T-2	Deliver report with findings; or
T-3	Create model, usability and system requirements for production
T-4	Deliver production model/system
T-5	Support deployment
Domain VII	**Model Lifecycle Management**
T-1	Document initial structure
T-2	Track model quality
T-3	Re-calibrate and maintain the model
T-4	Support training activities
T-5	Evaluate the business benefit of the model over time

Enterprise Business Processes and Decision Making | Data Management | Analytical and Modeling Tools

Source: Adapted from INFORMS (2014).

Second, the use of co-curricular experiences (as highlighted in Figure 6) has been a critical component of the program's success. As part of the program orientation, students are introduced to a company project sponsor (e.g., General Motors, Steelcase) as well as members from the IBM analytics support team who, in concert with university faculty, guide the students in performing their initial analytics project concurrently with their first courses. The IBM team provides students hands-on experience managing an analytics project, and formal general training and targeted guidance in using SPSS Modeler. This "being thrown into the fire" experience has resulted in students quickly identifying their knowledge gaps and knowing where they will have to differentially focus to develop the necessary depth across the three foundational areas. At the same time, IBM and the corporate sponsors have provided stellar support and guidance to the student teams so that teams are able to make actionable and meaningful recommendations to the corporate partner.

Third, as noted in Figure 6, the curriculum continues to evolve as we better understand the capabilities of our incoming students and the needs of the marketplace. For example, while we require that students have a formal understanding of statistics to get admitted to the program, we discovered that additional coverage of statistics was needed to get students to have the level of proficiency in model development and data mining that is required to be a successful data scientist. In addition, we have enhanced the emphasis on "marketing analytics" by deepening student skill sets in web and social media analytics. To accommodate these changes, we have incorporated the critical content of project management, and legal and ethical issues into existing courses or skills developed while conducting the experiential learning projects.

All graduates of our first cohort are employed full time with an average salary of $75,000. While our second cohort has not yet graduated, we have seen an increase in the average salary to $80,000. Students received offers representing a variety of companies including General Motors, Domino's Pizza, Capital One, and Ernst & Young. Students also received offers from companies that have sponsored projects, creating even greater synergy between the university and the sponsors. Overall, the mix of opportunities includes both corporate and consulting firms, and the job titles include Business Intelligence Developer, Data Analyst, Solutions Architect, and Consultant.

Graduates highlight the importance of integrating their newly learned diverse skills in the form of experiential projects as they transition from their university experience to their employers. They note that depth in one skill and not others is insufficient for success. Further, the graduates all highlight the importance of being able to effectively communicate findings and insights—to

Figure 5: Current curriculum and content of the MS program.

Introduction to Business Analytics (3) How digitized business processes and data analytics are essential to the performance and competitive advantage of a modern corporation. Different approaches for strategic data management and business analytics including relational databases, SQL, data warehouse concepts. Business process understanding using SAP. Application of business intelligence tools including Cognos.	Applied Statistics Methods (3) Application of regression models including simple and multiple regression, model diagnostics, model selection, one- and two-way analysis of variance, mixed effects models, randomized block designs, and logistic regression.	Data Mining (3) Techniques and algorithms for knowledge discovery in databases, from data preprocessing and transformation to model validation and postprocessing.
Intro Stats (2) Application of statistical concepts including random variables, distributions, parameter estimation, hypothesis testing, analysis of variance and time-series analysis. Develop modeling understanding of when to use what analytical capability.	Web Analytics (2) The collection and analysis of information from the web, including predicting future behavior, search engine optimization, landing page optimization, and mobile marketing and analytics.	Applying Analytics to Solve Business Problems (3) Application of data mining and analytical modeling techniques to solve corporate business problems (e.g., customer churn, customer loyalty, market segmentation) using data sets from within and across companies.
Computational Techniques for Large-Scale Data Analysis (3) Emerging issues in big data (e.g., collection, warehousing, preprocessing, and querying; mining, cluster analysis, association analytics; MapReduce, Hadoop; out-of-core, online, sampling-based, and approximate learning algorithms; model evaluation and applications, etc.).	Practicum (3) OR Internship Corporate analytics project or internship designed to integrate strategic business understanding with analytical and modeling skills. Manage project engagement with organization.	Capstone Project (3) Corporate practicum in the development and delivery of predictive data analysis for strategic decision making in organizations. Application of the principles and tools of analytics to real-world problems in R&D, marketing, supply chain, accounting, finance, and human resources management. Development and presentation of analytical insights and recommendations.
Communication Strategies for Analytics (1) Development of managerial level business communication skills. Communication strategy development in oral and written form.		Social Network Analytics (2) Analyzing social media to support organizational decision making, monitoring social media, measuring social media return on investment.
Intro to Marketing/Social Network Analytics (2) Develop understanding of marketing business processes that increasingly rely on analytics including customer acquisition, marketing segmentation, and understanding lifetime value. Use analytical tools to develop models to support these business processes.	*The colors correspond to the prior figure highlighting business processes and decision making (green), data management (tan), and analytical and modeling tools (blue). The yellow highlights integrative content across all three areas. The numbers in parentheses represent the number of credit hours.*	

executives and business process owners in firms—using appropriate language (e.g., presenting impact findings using visual display to executives and highly technical models to business process owners).

More on curriculum

In addition to the launch of the MS in Predictive Analytics program, the university is committed to developing analytics awareness and understanding across our very large undergraduate population. Given the number of credits associated with our business degree (across all majors, including SCM), there are insufficient credits available for a student to develop the depth of knowledge needed in data management and analytics, and modeling tools. However, we are using the business core courses to develop awareness and strategic understanding of the importance of using predictive analytics when making many business decisions, and we are providing hands-on touch points for every student using integrative experiences, as outlined in the following.

The university has initiated the process of integrating a common thematic module—cognitive computing—within each course making up the core business requirement that every business major must take (SCM, marketing, finance, human resources, information systems, statistics, and a strategy capstone). Specifically, students are exposed to cognitive computing using IBM's Watson technology, which adapts and learns based on user and inputs (IBM 2012; MSU Broad College 2014). As such, each course leverages the university's partnership with IBM Corporation and others to provide insights into how cognitive computing and, more broadly, predictive analytics fits within that functional area, culminating with a case study focused on cognitive computing in the strategy capstone. In addition, each major will look to develop functionally specific analytics content to develop student understanding of how analytics will augment and enhance business decision making in their area of study. For example, the core SCM course includes a discussion of how Watson can be used to facilitate and enhance supply chain decisions.

A further specific implementation of predictive analytics involves the integration of Cognos Insight (a management-oriented business intelligence tool) in the core information systems course. Cognos Insight enables managers to peruse large amounts of data with an easy to manipulate graphical user interface that relies on visualization of the data to identify interesting insights and facilitate drilling deeper into the data to more fully understand those insights. Every student conducts multiple analyses with the tool, and to meet industry needs, is required to communicate those findings using actionable, business-oriented analysis and recommendations.

Figure 6: Curriculum evolution over three iterations.

Spring 2013	Summer 2013	Fall 2013
Introduction to Business Analytics (3)	Applied Statistics Methods (3)	Data Mining (3)
Project Management (3)	Marketing Technology and Analytics (3)	Applying Analytics to Solve Business Problems (3)
Computational Techniques for Large-Scale Data Analysis (3)	Practicum (3)	Capstone Project (3)
Communication Strategies for Analytics (1)		Legal, Ethical, and Intellectual Property Issues (2)
Co-Curricular: Smart Project and Making Business Happen Speaker Series		

Spring 2014		Summer 2014	Fall 2014
Introduction to Business Analytics (3)		Applied Statistics Methods (3)	Data Mining (3)
Introduction to Statistics (2)	Project Management (1)	Marketing Technology and Analytics (3)	Applying Analytics to Solve Business Problems (3)
Computational Techniques for Large-Scale Data Analysis (3)		Practicum OR Internship (3)	Capstone Project (3)
Communication Strategies for Analytics (1)			Legal, Ethical, and Intellectual Property Issues (2)
Co-Curricular: Smart Project and Making Business Happen Speaker Series			

Spring 2015	Summer 2015	Fall 2015
Introduction to Business Analytics (3)	Applied Statistics Methods (3)	Data Mining (3)
Introduction to Statistics (2)	Marketing Technology and Analytics (2)	Applying Analytics to Solve Business Problems (3)
Computational Techniques for Large-Scale Data Analysis (3)	Practicum OR Internship (3)	Capstone Project (3)
Communication Strategies for Analytics (1)		Social Network Analytics (2)
Co-Curricular: Smart Project and Making Business Happen Speaker Series		
Introduction to Marketing/Social Network Analytics (2)	*Removed Project Management and Legal, Ethical and Intellectual Property Issues as Courses. Retained critical content in other courses.*	

Notes: Blue arrows represent changes across the first three years of the program. Shaded areas represent course modifications (yellow) and new course developments (green).

CONCLUSION

This article brought insight into the rapidly evolving domain of SCM predictive analytics and represents, to our knowledge, one of the first academic, large-scale surveys on the topic. With the data collected, we were able to provide a current assessment of the extent to which SCM predictive analytics are used in industry, together with the underlying motivations. We also identified primary benefits and major obstacles to SCM predictive analytics. In doing so, we offered additional insight into various usage groups and their characteristics, explicating the current state of data science, predictive analytics, and big data in SCM. Further, we provided recommendations on how to train our next-generation data scientists. Insight in this latter part was generated by the analysis of our survey data and expert interviews, combined with our experiences in developing and implementing one of the first MS degree programs in predictive analytics, offering insight into the future potential of data science, predictive analytics, and big data in SCM.

Overall, it was our intent to provide a timely assessment of the field and motivate additional research and pedagogical developments in this domain. As was illustrated, the field of SCM predictive analytics provides a promising avenue for transforming the management of supply chains, and offers an exciting array of research opportunities. For this purpose, and based on our insight derived from the survey, expert interviews, and the development of the MS program, we offer the following possible avenues for future investigation. From a strategic perspective, there is a need for understanding the specific types of supply chain questions that firms are addressing with analytics and the measured value of the insights derived from analytics' activities (e.g., return on investment). Similarly, more formal investigation into the barriers impeding the adoption and infusion of predictive analytics into the organization would be valuable. In addition, linked to the adoption of business analytics is the organizational structure that is implemented to promote and support enterprise analytics' activities. Associated questions in need of further investigation include the following: What are the differing impacts of having a centralized, distributed, or hybrid structure for successfully promoting analytics' use within the enterprise, and how might that structure change over time? What corporate governance structures need to be in place to enable and facilitate SCM predictive analytics? In addition, legal and ethical issues in the use of predictive analytics, especially as it pertains to consumer data, need to be investigated. Promising avenues for predictive analytics exist also in its application to real-time risk management and dynamic resource optimizations. It is our hope that this article provides motivation and a starting point to stimulate further research in SCM predictive analytics, and to further infuse curricula with predictive analytics components.

REFERENCES

Akkermans, H.A., and Van Wassenhove, L.N. 2013. "Searching for the Grey Swans: The Next 50 Years of Production Research." *International Journal of Production Research* 51 (23–24):6746–55.

Balboni, F., Finch, G., Rodenbeck Reese, C., and Shockley, R. 2013. *Analytics: A Blueprint for Value*. IBM Institute for Business Value, Executive Report, Somers, NY.

BISoftwareInsight. 2014. "Top Big Data & Analytics Masters Programs." http://www.bisoftwareinsight.com/resource-center/big-data-analytics-programs/

Cecere, L. 2012a. "Big Data – Go Big or Go Home?" *Supply Chain Insights* (July 1, 2012). http://supplychaininsights.com/wp-content/uploads/2012/07/Big_Data_Report_16_JULY_2012.pdf

Cecere, L. 2012b. "Voice of the Supply Chain Leader." *Supply Chain Insights* (May 28). http://supplychaininsights.com/voice-of-the-supply-chain-leader-2014/

Chae, B., Olson, D., and Sheu, C. 2014. "The Impact of Supply Chain Analytics on Operational Performance: A Resource-Based View." *International Journal of Production Research* 52(16):4695–710.

Dwoskin, E. 2014. "Big Data's High-Priests of Algorithms: 'Data Scientists' Meld Statistics and Software for Find Lucrative High-Tech Jobs." *The Wall Street Journal* (August 8). http://www.wsj.com/articles/academic-researchers-find-lucrative-work-as-big-data-scientists-1407543088

Hazen, B.T., Boone, C.A., Ezell, J.D., and Jones-Farmer, L.A. 2014. "Data Quality for Data Science, Predictive Analytics, and Big Data in Supply Chain Management: An Introduction to the Problem and Suggestions for Research and Applications." *International Journal of Production Economics* 154:72–80.

IBM. 2012. "Michigan State University to Introduce Students to Analytics and Big Data Using IBM Watson." *IBM News Release*. http://ibm.mediaroom.com/index.php?s=43&item=1453#

INFORMS. 2014. *Candidate Handbook*. https://www.informs.org/Certification-Continuing-Ed/Analytics-Certification/Candidate-Handbook

Jaspersoft. 2014. "Jaspersoft Big Data Survey Shows Rise in Commitment to Projects and Decline in Confusion." *Jaspersoft Press Release*. http://www.jaspersoft.com/press/jaspersoft-big-data-survey-shows-rise-in-commitment-to-projects-and-decline-in-confusion

LaValle, S., Lesser, E., Shockley, R., Hopkins, M.S., and Kruschwitz, N. 2013. "Big Data, Analytics and the Path From Insights to Value." *MIT Sloan Management Review* 52(2):21–32.

Lycett, M. 2013. "Datafication: Making Sense of (Big) Data in a Complex World." *European Journal of Information Systems* 22(4):381–86.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., and Byers, A.H. 2011. "Big Data: The Next Frontier for Innovation, Competition, and Productivity." *McKinsey Global Institute*. http://www.mckinsey.com/insights/business_technology/big_data_the_next_frontier_for_innovation

MastersInDataScience. 2014. "23 Great Schools With Master's Programs in Data Science." http://www.mastersindatascience.org/schools/23-great-schools-with-masters-programs-in-data-science/

McAfee, A., Brynjolfsson, E., Davenport, T.H., Patil, D.J., and Barton, D. 2012. "Big Data: The Management Revolution." *Harvard Business Review* 90(10):61–67.

MSU Broad College. 2014. "Broad Undergraduates Move Into Our Cognitive Computing Future With IBM's Watson." *MSU Broad College Press Release*. http://broad.msu.edu/2014/01/

22/broad-undergraduates-move-cognitive-computing-future-ibms-watson/

Nestler, S., Levis, J., and Klimack, B. 2012. "Certified Analytics Professional." *Analytics*, Sept/Oct, 26–29.

North Carolina State University. 2014. "Degree Programs in Analytics and Data Science." http://analytics.ncsu.edu/?page_id=4184

Russom, P. 2011. "Big Data Analytics." TDWI Best Practices Report, Fourth Quarter. http://www.sas.com/content/dam/SAS/en_us/doc/research2/big-data-analytics-105425.pdf

Waller, M.A., and Fawcett, S.E. 2013a. "Click Here for a Data Scientist: Big Data, Predictive Analytics, and Theory Development in the Era of a Maker Movement Supply Chain." *Journal of Business Logistics* 34(4):249–52.

Waller, M.A., and Fawcett, S.E. 2013b. "Data Science, Predictive Analytics, and Big Data: A Revolution That Will Transform Supply Chain Design and Management." *Journal of Business Logistics* 34(2):77–84.

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