BIG DATA ANALYTICS: ACCELERATING INNOVATION AND VALUE CREATION

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FINAL REPORT

Ajax Persaud, Ph.D

Sandra Schillo, Ph.D

Telfer School of Management

University of Ottawa

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KEY MESSAGE

Big data analytics refers to the ability of organizations to collect and analyze massive amounts of data (e.g., transactional, text, audio, videos, streaming) from many sources (e.g., social media, websites, sensors) to gain granular insights about people. Organizations could leverage these insights to accelerate innovation and value creation. Our review of the big data and analytics literature suggests that:

Big data analytics has ushered in a new era of innovation, value creation, productivity, growth, and competitiveness that has the potential to fundamentally alter the way we live, work, and think. Numerous economic and social benefits are being linked to big data analytics. These include improved operational efficiency and effectiveness, service delivery, cost control, fraud detection, and health-care provision.

The data deluge of big data will become even more massive in the future with the Internet of Things as billions of sensor-equipped devices are connected through the Internet. This data will be a gold mine that can generate tremendous socio-economic innovation and value creation.

Adoption of big data analytics is in its infancy and many organizations are uncertain as to how to organize and manage their big data initiatives to harness the value creation potential. One of the most difficult challenges for companies is how to build difficult-to-imitate big data analytics capability than can give them sustained competitive advantage and deliver business value. Developing a data-driven decision-making culture, where managers and workers alike make decisions based on data rather than intuition, seems to be a precondition for big data success but very difficult to accomplish.

Big data analytics is a socio-technical process involving technology, people, and processes. However, the greatest challenges to harnessing the value of big data analytics pertain to a wide array of people and process factors.

There is a tremendous gap between the supply and demand in Canada, the United States, and Europe for managers, analysts and workers with the requisite skills to take-up careers in big data analytics. Moreover, there is considerable ambiguity regarding the precise skills, talents, and capabilities needed for specific big data analytics positions. Narrowing the skills gap will require coordination among industry, universities and governments.

Big data analytics is a recent development and academic research into big data analytics is in its infancy despite the substantial growth in research over the last few years. The bulk of the literature focuses on the technical aspects such as infrastructure tools, technologies, platforms, services and processes with very little on the management, organization, and business aspects of big data analytics. Further, most of what we know about big data analytics is based on very large companies in the technology, finance, and retail sectors. Research on small and medium-sized enterprises (SMEs), particularly Canadian SMEs, is virtually nonexistent. Further, the bulk of management research on big data is descriptive and anecdotal. More research, particularly involving Canadian companies, is needed in order to better understand the issues and challenges they face in adopting big data analytics.

EXECUTIVE SUMMARY

The era of big data is unfolding at an unprecedented pace. New technologies and algorithms are enabling organizations to collect massive amounts data from multiple sources with unprecedented speed and to analyze this data to produce granular insights about human behaviours. These insights can lead to innovations that can create fundamental shifts in productivity, growth, commerce, service delivery, cost control, operating efficiency, customer value, and competitiveness. Big data and analytics can change the way we think, live, and work. However, harnessing the huge potential of big data requires a clear understanding of the characteristics of big data and the path from big data to ‘big impact’.

Big data refers to large, complex and distributed datasets that constantly evolve in content and representation while analytics refers to the application of advanced analytical techniques on big data to extract and visualize insights. The most widely used description of big data analytics emphasizes its 5Vs characteristics i.e. *volume, velocity, variety, veracity,* and *value*. Volume refers to massive amounts of data; velocity refers to the speed at which data is generated, variety refers to the diverse types and sources of big data, veracity recognizes that big data can have biases and inaccuracies, and value recognizes that raw data has low value until analytics is applied to gain useful insights.

Big data analytics has become a popular topic of discourse in the media and among industry executives, policymakers, and even academics over the last five years. The upbeat rhetoric surrounding big data analytics has been fueled by consultants, software vendors, management gurus, and others with vested interests in the commercial success of big data. Several metaphors have been used to signal its potential impact. These include *a revolution*, *a new era*, *a new paradigm, the new industrial paradigm, the next frontier, the new oil, enterprise assets*, and a *new economic asset*. Today, there is clear evidence that big data analytics has passed the stage of a fad and has become an institutionalized field with a vibrant ecosystem that promotes big data analytics practices and research.

Despite the of growth on the supply side of big data analytics (e.g., technology infrastructure and platforms and university training programs), some scholars argue that there is currently little conclusive evidence of its adoption by firms, governments, and non-profit organizations. There seems to be a fair bit of uncertainty around what data to collect, how best to collect, process, analyze and interpret it as well as how to transform insights into value. This observation seems to be supported by a recent survey by Deloitte of 200 senior executives of Canadian and US firms, which showed that only about 5% of Canadian firms and 17% of American firms have attained some level of analytics sophistication to be deemed insight driven organizations. Unfortunately, there is a severe dearth of empirical academic studies, particularly with respect to Canadian firms, regarding the adoption of big data analytics.

In this report, we synthesize the literature on five interrelated themes to determine the state of knowledge, and possible gaps, regarding the key factors that facilitate or inhibit an organization's ability to harness the value of big data. The themes are (1) the prerequisites for successful deployment of big data analytics, (2) the mix of knowledge, skills and capabilities for careers in big data analytics, (3) the application of big data analytics for creativity, innovation, and value creation, (4) the challenges in harnessing value from big data initiatives, and (5) the role of government policies in advancing big data analytics in the economy.

Deployment of big data analytics: The general view seems to be that failures of big data projects can often be ascribed to management and organizational issues rather than the characteristics of data or lack of technology. In order to deploy and harness the value of big data initiative, management scholars advocate that senior management must adopt a data-driven decision-making strategy and foster a data-driven culture across the organization. A data-driven culture is one where organizational members (including top-level executives, middle managers, and lower-level employees) make decisions based on the insights extracted from data rather than intuition or past practices. In other words, data-driven decision-making must permeate all levels of the organization regardless of job title, role or position since data and decisions are generated at all levels and by all processes of an organization.

Mix of knowledge, skills and capabilities for big data careers: Big data analytics span many disciplines including information science, mathematics, social science, system science, psychology, and economics. It employs techniques such as probability theory, machine learning, statistics, computer programming, data engineering, pattern recognition, visualization, data warehousing, and high-performance computing. Currently, there is an overwhelming focus on technical skills and far less emphasis on managerial or soft skills. This may be because we are in the early technology-intensive phase where the focus is on developing and perfecting the various tools, technologies, and infrastructure. The emerging evidence suggests that most big data analytics jobs require a unique combination of technical, managerial, and analytical skills. However, the specific combination of these skills may vary with the specific job requirement. Business skills include communication, project management, organizational, and multi-tasking skills. Analytical skills include problem definition, predictive analysis, data visualization and modeling skills, integrative, problem solving, and decision-making skills. Technical skills include software applications, languages, and big data infrastructure. Currently, there is a huge shortage of people with big data skills in Canada, the US, and Europe, even though universities and colleges are increasingly offering big data analytics programs and courses.

Application of big data analytics: The most common and easily identifiable application of big data analytics is on improving core function such as marketing, operations, supply chain, and human resources to make them more efficient and effective. The overwhelming focus is on achieving specific operational goals such as strengthening customer relationships, lowering management risk, and improving operational efficiency, which may lead to improved competitive advantage. On the other hand, truly big data analytics companies simply develop ecosystems devoted to compiling and accumulating data, which are subsequently monetized. Facebook is one such example. Additionally, an increasing number of organizations are utilizing machine-to-machine data derived from sensors to improve their services and launch new products, processes, and business model innovations. Applications using sensor and other data include smart cities, smart health, smart aging, and smart grids projects.

Challenges in harnessing value from big data: The challenges associated with creating and harnessing value from big data analytics initiatives pertain to data, technology, people, and processes. The data and technology challenges tend to be more technical in nature while the people and process challenges tend to be more management and business-oriented. Technical challenges can be solved more readily, however, management and business-oriented challenges appear more difficult and protracted to resolve. One of the most difficult challenges facing companies is how to build difficult-to-imitate big data analytics capability than can give them sustained competitive advantage and deliver business value.

Government policies: The capacity to accumulate, process, and utilize vast amounts of data will become a new landmark of a country's strength and competitiveness. This indicates that greater collaboration among government, industry, universities, and other sectors of the economy in data access and sharing could result in positive socio-economic development. Many countries around the world including China, the United States, France, the United Kingdom, Germany, and Canada have launched big data initiatives aimed at promoting their competitiveness, security and prosperity. Deepening such efforts will become even more important in the future.

Implications

This research shows that big data analytics has the potential to accelerate innovation, value creation and competitiveness of organizations. However, the path from data to value creation is not automatic, as more data does not naturally lead to greater value. Several technical and organizational challenges must be overcome along the way. Organizational challenges appear to be far more difficult to address than technical ones. This implies that organizations must take deliberate and early actions to identify and address organizational and managerial challenges. Another implication is that big data analytics is increasingly leading to the digitalization of management and work, whereby algorithms are increasingly performing the work of managers and employees. Organizations need to assess how this trend will affect them and develop strategies to address the impact. The current talent shortage appears acute. However, as universities and colleges offer more training programs, this shortage will abate. In the interim, managers have to seek alternative ways to secure the talents they need. From the perspective of government actions, it seems that closer collaboration among government, industry, universities, and other agencies in big data is an imperative. As big data analytics deepen in Canada, Government may need to develop a cadre of public service employees with the requisite big data analytics skills so that they can effectively serve businesses and citizens.

Future Research

This synthesis reveals many areas and topics for future big data analytics research. Some of these include: (1) Big data analytics challenges for Canadian companies, particularly since the adoption rate is dismally low; (2) Skills, talents, and capabilities for the future workforce in light of the increasing use of computers and algorithms to replace not only routine tasks but complex tasks and managerial functions; (3) Collaboration approaches among industry, government and universities to deliver academic and on-the-job training to ensure talent pools are equipped with the right skills to support the ever-changing big data analytics environment; (4) Empirical research on the value of big data analytics initiatives that can help managers better deploy and harness the value creation potential of their big data initiatives; and (5) Understanding how organizations can develop a culture that embraces data-driven decision-making across all levels and ranks.

BIG DATA ANALYTICS: ACCELERATING INNOVATION AND VALUE CREATION

CONTEXT

The era of big data is unfolding at an unprecedented pace. New technologies, analytical tools and algorithms are making it possible for organizations to collect and analyze massive volumes of a variety of data from multiple sources with unprecedented speed to produce granular insights about human behaviours. These insights can lead to innovations that can create fundamental shifts in productivity, growth, commerce, service delivery, cost control, operating efficiency, customer value, organizational performance and competitiveness (Sharma, Mithas, & Kankanhalli, 2014). Harnessing the huge potential of big data requires a clear understanding of the characteristics of big data and the path from big data to 'big impact'.

Current thinking is driven by the notion that bigger and better data *naturally* leads to better insights that *automatically* lead to greater value. The successes of a few large firms with deep resources, skills, and capabilities to achieve specific goals have reinforced this thinking. While there is some evidence that big data analytics *can* create value, the assumption that it *automatically* leads to value needs closer examination because there are many intervening processes and factors that can inhibit both a firm's ability to derive useful insights and subsequently convert the insights into value creation activities.

In this report, we synthesize the literature on five interrelated themes to determine the state of knowledge, and possible gaps, regarding the key factors that facilitate or inhibit an organization's ability to harness the value of big data. The themes are (1) the prerequisites for successful deployment of big data analytics, (2) the mix of knowledge, skills and capabilities for careers in big data analytics, (3) the application of big data analytics for creativity, innovation, and value creation, (4) the challenges in harnessing value from big data initiatives, and (5) the role of government policies in advancing big data analytics in the economy.

Big data and analytics has become a popular topic of discourse in the media and among industry executives, policymakers, and even academics over the last five years. The upbeat rhetoric surrounding big data analytics has been fueled by consultants, software vendors, conference organizers, management gurus, and others with vested interests in the commercial success of big data analytics (Madsen & Stenheim, 2016). Big data analytics was given a further boost when the academic community launched new, specialized journals and conferences on big data and published academic articles and books touting the merits of big data (Madsen & Stenheim, 2016). Further impetus was injected when many leading universities and colleges launched new academic and executive programs to cultivate big data analytics talents (Cegielski & Jones-Farmer, 2016; Jin, Wah, Cheng, & Wang, 2015). Additionally, big data analytics is driven by advances in computing technologies that are now faster, cheaper, and more powerful (Storey & Song, 2017).

Moreover, a variety of buzzwords and metaphors have been used to promote hype around big data analytics (Madsen & Stenheim, 2016). These include *a revolution*, *a new era*, *the next frontier*, *the new oil*, *enterprise assets*, and a *new economic asset* (e.g., Manyika et al., 2011; McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012; Russom, 2011). Many scholars posit that these metaphors serve as the rallying cry to facilitate action and drive organizational changes as it becomes easier to argue that changes are necessary because big data analytics is changing the business environment (Cluley, 2013; Harford, 2014; Madsen & Stenheim, 2016). They also conjure images of innovation and profits that are difficult to argue against (Madsen & Stenheim, 2016).

In light of these developments, Madsen and Stenheim (2016) claim that big data analytics has passed the stage of a fad and has become an institutionalized field with a vibrant ecosystem that promotes big data analytics practices and research (Ekbia et al., 2015). The strength of the ecosystem is rooted not only in the individual contributions of the different actors (e.g., consultants, software vendors, conference organizers, academics, elite educational institutions, and government policymakers) but also in the close cooperation and linkages among them (Ekbia et al., 2015; Madsen & Stenheim, 2016). For instance, IBM Watson Analytics has close ties with many universities and health care organizations and many technology vendors sponsor conferences, trade shows and offer speakers at these conferences (Ekbia et al., 2015; Madsen & Stenheim, 2016).

In spite the of growth of the supply side of big data analytics, some scholars argue that there is currently little conclusive evidence of the adoption of big data analytics by firms, governments, and non-profit organizations (Rigby & Bilodeau, 2011). According to Mazzei and Noble (2017), a considerable number of executives are still unsure how to properly apply big data analytics within their organizations due to uncertainties around what data to collect, how best to collect, process, analyze and interpret it as well as how to transform insights into value. They argue that a deeper understanding of the answers to these questions will assist executives in deploying resources and harnessing the benefits of their big data investments (Mazzei & Noble, 2017).

So, what exactly does “big data and analytics” mean? There is a mélange of definitions (Ekbia et al., 2015) with no universally accepted definition (Jin et al., 2015). Generally, big data refers to large, complex and distributed datasets that constantly evolve in content and representation while analytics refer to the application of advanced analytical techniques on big data to extract and visualize insights (Sharma et al., 2014). Other definitions focus on the high volume, velocity, and variety of information assets that demand new, innovative forms of processing for enhanced decision making and business insights (Schildt, 2017; Storey & Song, 2017). The most widely used description of big data analytics emphasizes its 5Vs characteristics i.e. *volume*, *velocity*, *variety*, *veracity*, and *value*. Volume refers to the magnitude of data that systems must ingest, process, and disseminate; velocity refers to the speed at which data is generated, analyzed and acted upon; variety refers to the diversity of data sources and formats whose content and representation constantly evolve; veracity recognizes that big data can have biases, ambiguities, and inaccuracies which need to be accounted for in order to reduce inference errors and improve the accuracy of generated insights; and value recognizes that big data in its raw form has low value until analytics are applied to gain useful insights (Gandomi & Haider, 2015; Laney, 2001; Lukoianova & Rubin, 2014; Sharma et al., 2014).

In an attempt to develop coherence among the disparate definitional perspectives, De Mauro, Greco, and Grimaldi (2016) and Ekbia et al. (2015) each classified the definitions into four distinct groups based on their main emphasis. De Mauro et al. (2016) identified definitions that focus on the *attributes* of big data such as the 5V characteristics, those that focus on the *technological requirements* such as the new technology and methods to process big data, those that focus on *thresholds* i.e. data whose volume exceeds a certain threshold, and those that focus on *social impacts* of big data. Ekbia et al. (2015) also highlighted four groups, namely, *product-oriented, process-oriented, cognition-oriented* and a *social movement* perspective. The product- and process-oriented definitions are very similar to De Mauro et al. (2016) attribute, technological requirements, and thresholds categories. The cognition-oriented perspective focus on the way human beings, with their particular cognitive capacities, can relate to big data while the social movement perspective focuses on the actions of both supply side actors to create a powerful big data ecosystem and the social impacts of big data.

Our synthesis suggests that most definitions emphasize the technical dimensions of big data and have neglected the human and organizational dimensions such as governance and culture that are equally important to reap the benefits of big data (Gupta & George, 2016). Moreover, the neglect of the social dimensions has resulted in a limited understanding of how organizations need to change to embrace these technological innovations, and the business shifts they entail (McAfee, Brynjolfsson, Davenport, et al., 2012). Essentially, the preoccupation with the technical characteristics of big data has resulted in the overwhelming majority of the academic literature being technology-oriented. However, the number of scholarly business and management studies on big data analytics has been on the rise over the last few years. However, most of these studies are conceptual in nature or based on anecdotal small case study evidence. Large scale empirical studies are currently the exception.

Boyd and Crawford (2012) note that more data and superior analytical methods do not necessarily equate to better insights and greater value. Indeed, the real potential of big data lies not in the data itself but in the insights generated and the value created from such insights (Markus & Tanis, 2000). In this context, Hayashi (2014) cautions that the era of computational prowess does not obviate the need for intuition and creativity, particularly at the problem-formulation stage. Recent reports from various consulting houses indicate that early adopters of big data analytics faced formidable challenges in harnessing the potential benefits of big data analytics. For instance, Capgemini (2016) reported that out of 210 executives of US and European companies, only 1 in 3 reported some benefits, 3 out of 5 did not meet costs and performance objectives, and a majority of the big data investments fail to pay off because most companies are either not ready or do not make decisions in response to the intelligence extracted from data (McAfee, Brynjolfsson, Davenport, et al., 2012; Ross, Beath, & Quaadgras, 2013). It seems that the path from big data to ‘big impact’ is not well-understood and that while big data analytics *can* create value, the assumption that it *automatically* leads to value needs closer examination.

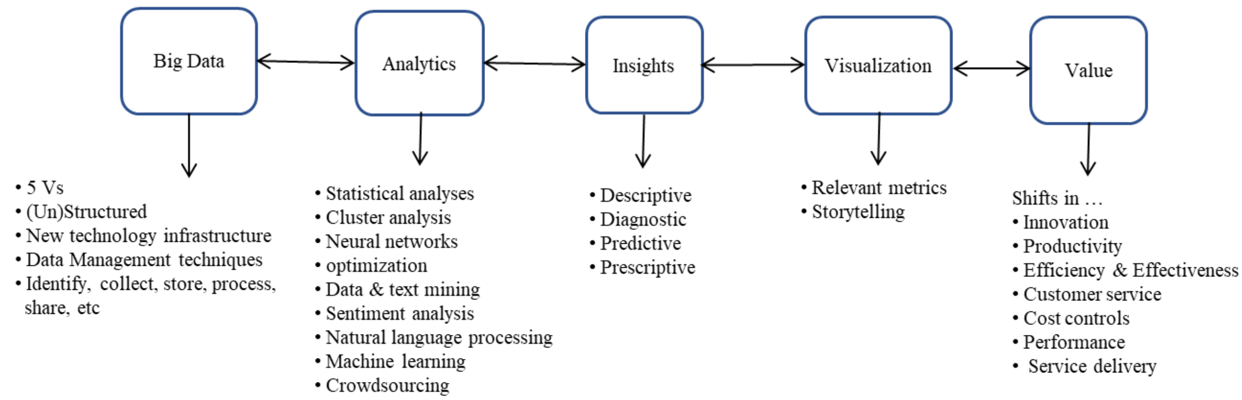
Gupta and George (2016) asserts that gaining competitive advantage from big data is more than simply collecting hordes of data and having access to sophisticated technology since all firms can imitate that. More importantly, it is also about having the availability of big data-specific technical and managerial skills, an intensity of organizational learning, and an organizational culture where insights extracted from data are valued and acted upon (Ross et al., 2013). It is the combination of all these resources that will create a firm-specific big data capability that can lead to competitive advantage. Marr (2015) and Ross et al. (2013) argue that big data analytics capability is not about data or technological advances but about improved organizational decision-making and performance.

Figure 1 presents a conceptual model of big data analytics based on a synthesis of the literature. This model can be considered as a top-level value-chain model from data collection to value creation (Gandomi & Haider, 2015; Sharma et al., 2014). It does not show the detailed processes relevant at each stage along with the respective feedback loops. The first two stages are concerned with data management and analytics while the remaining three phases focus on insight generation, insight visualization and presentation, and value creation. The data management phase focuses on capturing, storing and preparing the data while the analytics phase uses advanced analytics techniques to derive insights by conducting four types of analytics: (1) descriptive analytics to answer the question - what happened? (2) diagnostic analytics to answer the question - why did it happen? (3) predictive analytics to answer the question– what will happen? if a course of action is taken, and (4) prescriptive analytics to answer the question – how can I make it happen? (Hayashi, 2014).

Several management scholars (e.g., McAfee, Brynjolfsson, Davenport, et al., 2012; Ross et al., 2013; Sharma et al., 2014) argue that while advanced analytics could generate insights, it does not necessarily follow that top managers will accept or use the insights. Moreover, even if the insights lead to better decisions, it may not necessarily lead to better value or outcomes because of several intervening factors. For example, Sharma et al. (2014) noted that insights may point to multiple options and managers have to allocate resources for the chosen option. Depending on the resources at their disposal, they may choose options that match their resource constraints or seek additional resources from top management. This could lead to no action or choosing the lower value option, depending on the level of top management support (Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015). Further, even if managers were to choose the option that generates the best value and secures the necessary resources, implementing it may be the responsibility of a different group within the firm and they may not necessarily 'accept' the option or may even resist implementation (Mithas, Lee, Earley, Murugesan, & Djavanshir, 2013).

Some of the key managerial issues and challenges throughout this process involve the firm's strategy, structure (governance mechanisms), culture, people (talents and capabilities), resource orchestration and allocation decisions, incentives, top management support, and technology infrastructure (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Mithas et al., 2013; O'Reilly & Paper, 2012; Wamba et al., 2015; Woerner & Wixom, 2015).

Figure 1 Big Data Analytics Model



Implications

This research shows that big data analytics has the potential to accelerate innovation, value creation and competitiveness of organizations. However, the path from data to value creation is not automatic, as more data does not naturally lead to greater value. Several technical and organizational challenges must be overcome along the way. Organizational challenges appear to be far more difficult to address than technical ones. This implies that organizations must take deliberate and early actions to identify and address organizational and managerial challenges. Another implication is that big data analytics is increasingly leading to the digitalization of management and work, whereby algorithms are increasingly performing the work of managers and employees. Organizations need to assess how this trend will affect them and develop strategies to address the impact. The current talent shortage appears acute. However, as universities and colleges offer more training programs, this shortage will abate. In the interim, managers have to seek alternative ways to secure the talents they need. From the perspective of government actions, it seems that closer collaboration among government, industry, universities, and other agencies in big data is an imperative. As big data analytics deepen in Canada, Government may need to develop a cadre of public service employees with the requisite big data analytics skills so that they can effectively serve businesses and citizens.

Future Research

This synthesis reveals many areas and topics for future big data analytics research. Some of these include: (1) Big data analytics challenges for Canadian companies, particularly since the adoption rate is dismally low; (2) Skills, talents, and capabilities for the future workforce in light of the increasing use of computers and algorithms to replace not only routine tasks but managerial functions and complex tasks; (3) Collaboration approaches among industry, government and universities to deliver academic and on-the-job training to ensure talent pools are equipped with the right skills to support the ever-changing big data analytics environment;

(4) Empirical research on the value of big data analytics initiatives that can help managers better deploy and harness the value creation potential of their big data initiatives; and (5) Understanding how organizations can develop a culture that embraces data-driven decision-making across all levels and ranks.

Methodological Approach

This objective of this study is to identify and synthesize the current scholarly research on big data analytics in the context of the management and business. The four-phase, systematic approach outlined in (Kitchenham et al., 2009) was utilized. These stages are: (1) Searching for relevant studies using automatic and manual procedures, (2) Evaluating the retrieved publications against the validated inclusion and exclusion criteria, (3) Extracting the relevant information from selected studies, and (4) Synthesizing the studies to draw conclusions and interpret the findings. The search terms used to conduct automatic searches on various management and business databases were “big data” and “analytics”. The databases searched were ABI Inform Global, Scopus, Web of Science, and Business Source Complete. These databases cover virtually all high-quality business and management journals and academic conference proceedings. The search results were evaluated against predetermined inclusion and exclusion criteria. Inclusion criteria included, for example, academic journals and conferences in English and a focus on management and business issues. Exclusion criteria were, for example, excluding non-English articles and those focussing on the technical aspects of big data i.e. engineering, computer science, and mathematics. The search results were further narrowed by reading the titles and abstracts. Only those that appeared relevant were retained and stored in Endnotes, a reference manager. Duplicates from the various databases were removed and then the full texts were scanned for their relevance. Manual search was also conducted by examining the reference list of the articles selected. Eventually, we uncovered forty-five relevant articles. These articles form the basis of this synthesis report. Given the limited number of empirical academic articles found, it was decided that recent publicly available reports from consulting houses would be included in order to derive insights from practitioners’ perspectives.

RESULTS

Theme 1: Prerequisites for successful deployment of big data analytics

Management scholars and organization theorists have postulated that big data analytics will create fundamental shifts in organizing and management (Autor, 2015; Constantiou & Kallinikos, 2015; Zuboff, 2015) because they can directly shape the internal workings of organizations and management practice (Huber, 1990; Schildt, 2017; Zammuto, Griffith, Majchrzak, Dougherty, & Faraj, 2007). For instance, big data analytics will reshape work and the value of skills (Autor, 2015) by deskilling certain workers and requiring new and different skills to work in a big data analytics environment (Cegielski & Jones-Farmer, 2016; Davenport, 2014; Schildt, 2017; Vidgen, Shaw, & Grant, 2017; Wamba et al., 2015). Brynjolfsson and McAfee (2014) argue that artificial intelligence and natural language processing will reshape many industries as organizations utilize computers and data to perform increasingly complex tasks, faster and cheaper than humans (Schildt, 2017). Thus, organization theorists must address the potent effects that big data is already having on organizing and management (George, Haas, & Pentland, 2014).

Generally, organizational design is concerned with the governance structures, processes, policies, roles, responsibilities, and incentives that help an organization execute its strategy (Daft, 2012). The culture of an organization is also an essential component since it not only facilitates or hinders coordination (Nadler, Tushman, & Nadler, 1997) but also confer sustained competitive advantage (Barney, 1986a). Many scholars argue that these components of organizational designs are central for deploying and harnessing the value of big data analytics.

Garud, Kumaraswamy, and Sambamurthy (2006) contend that big data analytics are already enabling new forms of organizing. For instance, algorithms are at the core of the world's most innovative and valuable companies such as Amazon, Facebook, Google, Netflix and Uber (Schildt, 2017). In these firms, power shifts from the hierarchy of managers to larger cadres of professionals who master analytics, programming, and business (Schildt, 2017). As management routines shift from humans to technological systems, the room for creative adaptation is likely to decrease (Pentland, Feldman, Becker, & Liu, 2012). Schildt (2017) asserts that we will continue to witness the increasing 'digitalization of management' as advanced algorithms and the ability to process real-time data enable companies to build 'routine smartness' in their operations and eliminate many routine jobs. Workers will have to acquire new skills or undertake different tasks (Schildt, 2017). Lee, Kusbit, Metsky, and Dabbish (2015) predict that as 'algorithmic management' of work (management functions replaced by algorithms) deepens, governance itself will be made obsolete through total control provided by data (Zuboff, 2015). This is already evident in firms, such as Uber where algorithms make underperforming employees redundant without human intervention (Schildt, 2017).

Further, Davenport (2014) observe that data-driven decision-making strategy leads to changes in organizational culture, leadership, human resource management and other management practices. These changes could result in stronger customer relationships, lower management risks, and improved operational efficiency, which could ultimately improve a firm's competitive position (Sheng, Amankwah-Amoah, & Wang, 2017). Organizational alignment with data-driven strategy emphasizes the potential changes in organizational ecosystem and management processes as a result of big data strategy (Bean & Kiron, 2013). From strategic management perspective, big data is increasingly viewed as enterprise assets, which is critical for organizational success (Russom, 2011). It must be aligned with other resources and capabilities and configured in a manner that not only aid decision-making but improve organizational performance and provide sustained competitive advantage (Barney, 1986b, 2001; Bean & Kiron, 2013; Vidgen et al., 2017). Data-driven decision-making may enhance firm success but it requires substantial changes in organizational design elements such as structure, culture, incentive, roles, and coordination, and must be aligned with the organization's strategic mission (LaValle et al., 2011; Marshall, Mueck, & Shockley, 2015).

Several scholars argue that failures of big data projects can often be ascribed to management and organizational issues rather than technology (Akter et al., 2016; Ferguson, 2013; LaValle et al., 2011; O'Reilly & Paper, 2012; Sharma et al., 2014; Vidgen et al., 2017; Wamba et al., 2015;

Woerner & Wixom, 2015). Vidgen et al. (2017) observed that many organizations are still at a reactive 'baseline analytics' stage struggling with the issues of the data itself and not necessarily addressing business issues. In this regard, a survey of 200 Canadian and US organizations in 2017 by Deloitte revealed that only about 5% of Canadian firms and 17% of US firms can be classified as insight driven (Deloitte, 2017). Vidgen et al. (2017) lend support to this perspective by positing that big data analytics is not a technical project that should be given solely to the IT department but rather as a business transformation undertaking that requires an analytics strategy, top management support, and careful change management. In this context, IT functions as a key enabler of big data analytics processes and practices.

In the big data analytics literature, a very common theme is the importance of organizational culture, and more importantly, a data-driven organizational culture (Agrawal, 2014; Davenport, 2014; Ferguson, 2013; Gupta & George, 2016; LaValle et al., 2011; Marshall et al., 2015). Building off the strategy literature (e.g., Barney, 1986a), these scholars argue that a data-driven organizational culture is critical for achieving sustained competitive advantage and harnessing the value of the firm's big data investments (Gupta & George, 2016). For instance, LaValle et al. (2011) postulate that big data projects are often unproductive not necessarily because of the characteristics of data and lack of technology but rather the lack of a strong data-driven culture. In similar vein, Ross et al. (2013) suggest that culture has the ability to inhibit (or enhance) an organization's ability to benefit from big data. McAfee, Brynjolfsson, and Davenport (2012) view a data-driven culture as one where organizational members (including top-level executives, middle managers, and lower-level employees) make decisions based on the insights extracted from data. In other words, data-driven decision-making permeates all levels of the organization regardless of job title, role or position (Gupta & George, 2016). Malik (2013) asserts that data and decisions are generated at all levels and by all processes of an organization; thus, making it an organization-wide phenomenon, which makes it difficult to challenge.

In summary, it is apparent that deploying big data analytics and harnessing its full benefits in terms of value creation, innovation, and competitive advantage is an organizational-wide phenomenon requiring a strong data-driven culture. Moreover, it seems that the inability of firms to reap the full benefits of their big data analytics investments has more to do with organizational and management practices i.e., people and process issues rather than the characteristics of the data and technology. Further, it seems that big data analytics coupled with powerful information and communications technologies are increasingly performing a range of management functions as well as routine and even certain complex work usually performed by employees. In some senses, both employees and managers are being deskilled and will need different talents to undertake work in the future big data analytics era.

Theme 2: Mix of knowledge, skills and capabilities for careers in big data analytics

This section of the report examines the literature on the types of skills and talents needed for careers in big data analytics. It also reports on the supply and demand of such skills.

The field of big data analytics spans many disciplines such as information science, mathematics, social science, system science, psychology, and economics (Jin et al., 2015). It also employs techniques from many fields including probability theory, machine learning, statistical learning, computer programming, data engineering, pattern recognition, data visualization, data warehousing, and high-performance computing (Jin et al., 2015). Comuzzi and Patel (2016) argue that big data analytics goes well beyond data warehousing and business intelligence although both of these are utilized in big data analytics. These scholars contend that the differences between big data analytics and these techniques are substantial enough to require people to acquire specific new skills and talents in order to pursue big data analytics careers. This view is widely advocated in the literature (e.g., Cegielski & Jones-Farmer, 2016; Davenport, 2014; Dubey & Gunasekaran, 2015; Manyika et al., 2011; Power, 2016). The general thrust of the argument is that big data analytics requires a different, even unique, set of technical, managerial, and analytical skills that were not required with predecessor technologies such as business intelligence and data mining.

According to Gupta and George (2016) and Power (2016), the specific technical and managerial talents required for careers in big data are two sides of the same big data analytics coin. On the one hand, technical big data analytics skills refer to the know-how required to use new forms of technology to extract intelligence from big data. Some of these skills include competencies in machine learning, data extraction, data cleaning, statistical analysis, and understanding of programming paradigms such as MapReduce (Cegielski & Jones-Farmer, 2016). On the other hand, managerial skills are highly firm-specific and are developed over time by individuals working in the same organization and as a result of strong interpersonal bonds between organizational members (Gupta & George, 2016). Thus, within the context of a firm's big data function, the insights obtained from data will be of little use to an organization if its managers fail to foresee the potential of newly extracted insights (Gupta & George, 2016; Lycett, 2013; Sharma et al., 2014). Thus, it is imperative for managers to have a clear understanding of how and where to apply the insights extracted by their technical teams. On the flip side, technical analysts must be able to understand the questions asked by managers when they are seeking insights (O'Reilly & Paper, 2012).

According to Tambe (2014), during large waves of new IT innovations such as big data analytics, there are usually systematic differences in demand and growth rates across labor markets for specific talents. In these situations, data-intensive labor markets or early adopters of big data analytics tend to face significant difficulties acquiring the technical skills required to support big data tools (Tambe, 2014). In this context, the 2011 McKinsey Global Institute Report estimated a shortage of between 140,000 and 190,000 workers with deep analytical skills and a 1.5-million-person shortage of data literate managers. The report further estimated that by 2015 there would be 4.4 million jobs created to support big data (Manyika et al., 2011). Similar estimates by the European Commission predict a shortfall of about 900,000 IT workers by 2020. It was further estimated that 32 percent of Europe's workforce has insufficient digital skills (MacDonnel & Castro, 2016). In Canada, early estimates project just under 20,000 jobs (ICTC, 2016). The thrust of these projections seems somewhat similar—everyone from the new hire to the mid-career manager to the executive in the C-suite needs analytic skills.

Two important questions that have received little attention, particularly in the empirical academic literature, are: (1) what precise set of knowledge, skills, and capabilities are required for various classes of big data analytics jobs? and (2) how can employers seeking these skills acquire such skills in a tight labour market? We now explore the current state of knowledge on these two questions.

In terms of skills, talents, and capabilities for big data analytics careers, Cegielski and Jones-Farmer (2016) reported that there are considerable ambiguities and uncertainties among both employers and training institutions (e.g., universities and colleges) as to the precise needs. For example, Power (2016) claims that data analysts, decision-support designers and data scientists need to learn many new skills, and need to understand industry- or customer-specific analyses and systems, while (Reaney, 2014) suggests that some skills overlap across data roles, and some are particular to specific roles. Nevertheless, the supply of big data analytics skills is improving as universities and colleges tweak their existing courses and programs or develop big data analytics-specific programs (Cegielski & Jones-Farmer, 2016; Power, 2016).

In an attempt to signal the new knowledge, skills, and capabilities required for big data analytics careers, technology vendors and managers have developed several new job titles. These include Chief Data Officer, Data Scientists, Data Architects, Data Engineers, Data Analysts, and Decision-support Designers (Cegielski & Jones-Farmer, 2016; Dubey & Gunasekaran, 2015; Jin et al., 2015; Power, 2016). In addition to these specific job titles, several roles or types of data professionals have been suggested. For example, Reaney (2014) identified four types of big data analytics professionals: (1) data business people who lead and manage data initiatives; (2) data creatives who identify new data sources; (3) data analytics developers, programmers and engineers; and (4) data researchers, scientists and statisticians who analyze and interpret data. Similarly, Cegielski and Jones-Farmer (2016) suggest that big data analytics professionals fall into one of three categories, namely, deep knowledge analysts, data-savvy users, and technology support specialists.

In Cegielski and Jones-Farmer (2016) schema, deep knowledge analysts must have advanced statistical training to perform analysis on large datasets with cutting edge applications; data-savvy users are capable of interpreting data and making operational and strategic decisions that drive business, and technology support specialists possess technology skills to design, develop, and maintain hardware and software associated with big data. These authors observed that the three groups of professionals need business, analytical, and technical skills to varying degrees depending on their specific role. Business skills include communication, project management, multi-tasking, organizational, and self-directed skills. Analytical skills include problem definition, predictive analysis, data visualization, modeling, problem solving, and decision-making skills. Technical skills include applications (e.g. Excel, SAS, Tableau, Cognos, Rapid Miner), languages (R, Python, SQL, Java), and infrastructure (e.g. Hadoop, Casandra, Oracle, MapReduce, Hive, Pig).

According to Power (2016), data scientists should be prepared to perform three primary tasks: (1) *discover*, find, and identify the sources of good data, and appropriate metrics. Sometimes, request the data to be created and work with data engineers and business analysts; (2) *access* the data; and (3) *distill* and extract meaning from data, create decision relevant information to increase return on Investment (RoI) and take actions. They should be able to perform descriptive, diagnostic, predictive, and prescriptive analyses (Power, 2014). Additionally, Davenport and Patil (2012) recommend data scientists should have the skills of a database designer, software programmer, statistician and storyteller to explore the new data streams for decision-relevance. Data engineers extract, transform and load data, while data scientists access that data, distil it and discover new patterns.

According to Mikalef, Framnes, Danielsen, Krogstie, and Olsen (2017), a critical part for the success of a big data project is the support received from top management (Vidgen et al., 2017). In this regard, the Chief Data Officer (CDO) has emerged as someone responsible for managing the data asset for purposes of governance and innovation. The Chief Data Officer must be able to provide vision and strategy for data management initiatives.

In terms of skill acquisition, Tambe (2014) noted that hiring employees from other firms is a particularly important channel through which to acquire expertise. However, as big data analytics technologies mature and alternative channels emerge through which workers can acquire the complementary skills (e.g., university degree programs), the demand for such skills will weaken (Tambe, 2014). Recent market evidence indicate that big data analytics technologies are maturing, and the channels through which to acquire the complementary skills, such as university programs, are expanding (Cegielski & Jones-Farmer, 2016). Policies that accelerate the establishment of courses in business analytics by institutions providing education or training can narrow the imbalance between supply and demand. However, inequality in the stock of complementary skills across labor markets may result in faster productivity growth for firms in big-data-intensive labor markets relative to firms in non-intensive big-data market as people move to take up new job opportunities (Tambe, 2014). The social impacts of such situations could be quite profound particularly for these usually smaller non-intensive big-data market. Thus, it seems rather obvious that talent management decisions in the big data era are crucial for organizations in tight labor markets.

Summarizing the embryonic literature on the knowledge, skills, and capabilities of required for various types of big data analytics careers, it is rather clear that there is an overwhelming focus on required technical skills and far less research on the soft and managerial skills. We surmise that this may be due to the notion that we are in the early technology-intensive phase of big data analytics where the focus is on developing and perfecting the various tools, technologies, and infrastructure (Deloitte, 2017; Vidgen et al., 2017). However, in light of earlier findings that the real value of big data analytics lies not in the data itself but in the insights generated and the managerial actions taken, greater attention needs to be devoted to understanding the soft skills and managerial talents needed to reap the benefits of big data analytics investments. This is particularly important given that current evidence indicate that the majority of early big data analytics adopters are experiencing tremendous difficulties harnessing the value of big data analytics (Capgemini, 2016).

Theme 3: Application of big data analytics creativity, innovation, and value creation

In this section, we report on the literature regarding the nature and extent of application of big data analytics in firms to achieve organizational goals pertaining to innovation, creativity, productivity, growth, competitiveness and enhanced performance.

The literature reveals considerable evidence that big data analytics has been focused around the functions of operations management, human resources, and information technology management (e.g., Chen, Chiang, & Storey, 2012; Erevelles, Fukawa, & Swayne, 2016; Mithas et al., 2013). Moreover, significant impacts of big data can be seen in strengthening customer relationships, lowering management risk, and improving operation efficiency, which may lead to more effective marketing strategies and operations management to gain competitive advantages (Bean & Kiron, 2013; Ransbotham, Kiron, & Prentice, 2016)

In contrast, Mazzei and Noble (2017) posit that big data insights can influence not only operational or functional level decisions but also strategic management decisions. For instance, firms are leveraging their big data analytics resources to overcome traditional barriers to entry. The ultimate goal of big data adopters is to strengthen their dynamic capabilities and to employ big data analytics to secure sustainable competitive advantage through the development of diverse ecosystems and data flows (Mazzei & Noble, 2017).

In assessing how firms use big data analytics to achieve organizational goals, Mazzei and Noble (2017) classified firms into three tiers based on how they perceive and use big data analytics Tier 1 firms use data as a tool, Tier 2 firms perceive big data as an industry, and tier 3 firms use data as a strategy. Few firms have been able to combine all three perspectives; but those that can do so, stand to upend competition.

Tier 1 - Data as a tool - firms are focused on improving core function performance. This is the most easily identifiable application of big data analytics. Access to data is viewed as a gateway that allows executives to solve traditional value chain problems more efficiently and effectively. Examples of Tier 1 companies that use big data analytics to achieve specific operational goals include Coca Cola, Intel, Capital One, and Progressive Insurance. For instance, Progressive Insurance is using real-time analytics from in-vehicle telecommunications devices to monitor driving activity, creating a competitive advantage by identifying risky behaviors. This allows the company to rate each driver more accurately based on their actual driving habits, while also encouraging positive changes in the driving behaviors of its consumers (Mazzei & Noble, 2017).

Tier 2 - Data as an industry – firms focus on providing big data analytics services to existing businesses that either lack the technical and human resources to develop in-house big data analytics capabilities or are not interested in investing in such capabilities. This new breed of ventures specializes in the development, provision, maintenance, and sale of the hardware, software, infrastructure and the associated services to handle an organization's big data and analytics needs. These big data companies deliver novel value in an industry that did not exist 10 years ago and generate new job types that require cutting-edge skills (Mazzei & Noble, 2017). Companies like Palantir, Pivotal, SQream, and Cloudera provide big data products or services to a broad range of companies unable or unwilling to develop them internally (Mazzei & Noble, 2017). In the era of cloud computing, the other side of the big data analytics coin, these companies provide *Software as a Service*, *Platform as a Service*, *Infrastructure as a Service*, and *Analytics as a Service,* utilizing various deployment models such as private, public or hybrid (Storey & Song, 2017).

Tier 3 - Data as strategy - firms focus on data as central to their organizational strategy (Davenport, Barth, & Bean, 2012). These companies develop ecosystems devoted to their products and services based on the data they accumulate and consider the compilation of data as a source of value creation in and of itself (Mazzei & Noble, 2017). They do not need to monetize data immediately, for if they capture enough data it can be leveraged in innumerable—–and perhaps currently unrealized—– ways in the future as they broaden and navigate new industries as part of the development of their dynamic capabilities and digital ecosystem (Mazzei & Noble, 2017). Examples of these are Facebook, Apple, and Alphabet. The authors contend that there are few examples of firms that combine all three approaches. In their view, Amazon offers an iconic example of how a firm might apply data and analytics to evolve strategically and mature across all three tiers (Mazzei & Noble, 2017).

Additionally, there are many ongoing, and interesting real-world research projects that are based on effective use of big data analytics in the social sector. These include smart cities, smart health, smart aging, and smart grids (Storey & Song, 2017). Many of these applications of big data analytics utilize machine-to-machine analytics, an area of big data analytics that is set to grow tremendously with the Internet of Things as billions of devices are equipped with sensors and connected via the Internet (Ehret & Wirtz, 2017).

There has been tremendous advancement in sensor technologies that go into machines, automobiles, mobile devices, utility grids and enterprise networks. This has led to the generation of machine-to-machine (M2M) data at an unprecedented rate and in real-time (Ehret & Wirtz, 2017). Companies can use the data emitted by sensors from a wide variety of applications to analyze and improve efficiency of manufacturing processes, predict device failures and identify opportune times to up-sell new products to customers. The data can also provide insights for product development, customer support and sales teams who use the information to, for example, improve product features, increase revenues and lower costs (Svilar, Chakraborty, & Kanioura, 2013). The insurance industry is one example where sensor technologies are combined with telematics to offer consumers more tailored packages and develop new business models (Mazzei & Noble, 2017; Storey & Song, 2017).

The big data exhaust coming from sensors in devices represents a huge gold mine for data scientists to discover hidden patterns and provide deep insights that can benefit businesses, government and overall society (Svilar et al., 2013). Companies are analyzing these sensor data with advanced statistical techniques to gain real-time insights, and visualize possible scenarios using predictive analytics (Svilar et al., 2013). Local governments and healthcare providers are making extensive use of sensor data in smart cities projects and smart aging initiatives (Storey & Song, 2017). Another important application is to monitor the usage of devices and products by customers and provide pro-active alerts and triggers to the sales team on the right time to contact the customer for a product upgrade/refresh. This can be very effective to build a 1-2-1 relationship with the customer and help cross-sell and up-sell to the customer (Svilar et al., 2013).

Similarly, researchers are also developing models that combine clickstream data and weblogs with publicly available data to provide more timely insights on a wide variety of issues. For example, The Billion Prices Project (BPP) at the Massachusetts Institute of Technology led by economists Alberto Cavallo and Roberto Rigobon calculates a daily inflation index from a continuously evolving basket of goods (Armah, 2013). Data are collected with software that scours the websites of online retailers. The model provides a real-time inflation index that could offer policy-makers and statistical agencies a glimpse of what is happening to inflation in real time rather than weeks or months later as is currently the case. Other applications include collecting unemployment and welfare-related searches to improve predictions of initial claims for unemployment benefits as well as housing-related searches to predict housing sales in the United States (Armah, 2013).

In summary, we note that a wide variety of big data, both structured and unstructured, is being employed to gain insights on various economic and social issues that result in major innovations in service delivery, efficiency, and value creation. Indications are that as big data analytics technologies, tools, and techniques mature, we will see more applications in more areas of our lives. These applications are already having an impact on the way we think, live and work.

Theme 4: Challenges in harnessing value from big data initiatives

The challenges associated with creating and harnessing value from big data analytics initiatives pertain to data, technology, people, and processes. The data and technology challenges tend to be more technical in nature while the people and process challenges tend to be more management- and business-oriented.

There are many data challenges associated with deriving intelligence from big data. According to Storey and Song (2017), many analysts and decision-makers find it particularly difficult to comprehend the scale, velocity, and variety of big data and most businesses are unable to use much of the data generated. Moreover, the variety and veracity of data make it very challenging in developing software solutions. Gupta and George (2016) citing prior research reported that most organizations found unstructured big data, data storage and data transport as long-term technology issues to be addressed. Additionally, firms must deal with challenges pertaining to the integration of internal (e.g., transactional records) and external data (e.g., social network data). Gupta and George (2016) postulate that as big data technologies mature these data challenges will increasingly become less challenging.

Additional data challenges that could prevent companies from harnessing the potential of big data were highlighted by Jin et al. (2015). These pertain to data complexity, computational complexity, and system complexity. Data complexity refers to the inherent complex types, complex structures, and complex patterns of big data that makes its perception, representation, understanding and computation far more challenging relative to traditional computing models. Computational complexity refers to the variety, volume, and velocity characteristics of big data that make it difficult for traditional computing methods to effectively support the processing, analysis and computation of big data. System complexity refers to the design of system architectures, computing frameworks, processing modes, and benchmarks for highly energy-efficient big data processing platforms (Jin et al., 2015). Further, these authors argue that for big data projects to be successful, it is necessary to clearly articulate the requirements, regardless of whether they are technical, social, or economic.

Gupta and George (2016) contend that despite extensive media attention, there is little knowledge about how organizations build big data analytics capabilities. In their view, the primary challenge facing business leaders is how to make the best use of big data instead of the characteristics of big data. Many scholars assert that the majority of the big data investments fail to pay off because most companies are either unprepared or do not make decisions based on the insights extracted (Ross et al., 2013). Several other people and process challenges were identified that prevented managers from harnessing the value of their big data investments. One challenge that has received considerable attention is the difficulties organizations face in developing an organizational-wide data-driven decision-making culture that permeates all levels of the organization but particularly senior-level executives (Ferguson, 2013; Hayashi, 2014; Marshall et al., 2015; McAfee, Brynjolfsson, Davenport, et al., 2012; Vidgen et al., 2017; Wamba et al., 2015). Another widely-cited hurdle affecting the success of big data initiatives pertain to the lack of top management support (Mithas et al., 2013; Sharma et al., 2014; Vidgen et al., 2017; Wamba et al., 2015). Also, the lack of talent or the difficulty in hiring employees with big data-specific skills has been particularly challenging especially for early adopters of big data or in geographies that are considered data-intensive markets (Cegielski & Jones-Farmer, 2016; Gupta & George, 2016; Manyika et al., 2011; Tambe, 2014). Finally, many companies are finding it very challenging to monetize their big data analytics initiatives, that is, to figure out what all the data they have is worth in monetary terms (Najjar & Kettinger, 2013) as they do with other intangibles such as their brands, patents, trade secrets, and other intellectual properties (Hayashi, 2014).

The preceding discussion suggests a bifurcated focus on the challenges facing managers – those that pertain to data and technical challenges and those that pertain to people and processes or managerial challenges. Mikalef et al. (2017) suggest that while both categories of challenges are undoubtedly relevant, it is important for organizations to focus on the full range of resources which are needed to build a difficult to replicate big data analytics capability and try to understand through what mechanisms and under what conditions it can deliver business value (George et al., 2014; Gupta & George, 2016). It seems that a firm needs a unique blend of its financial, physical, human, and organizational resources to create a capability, which will be difficult to match by competitors (Vidgen et al., 2017; Wamba et al., 2015; Woerner & Wixom, 2015). Moreover, firms need to continuously reconfigure their resources according to changing market conditions (Bean & Kiron, 2013; Bughin, 2016; Vidgen et al., 2017). However, to do so, it is imperative for firms to be aware of the various resources that are required to build a capability (George et al., 2014; Gupta & George, 2016; Hayashi, 2014; Ross et al., 2013; Vidgen et al., 2017).

Theme 5: Government Policies and Big Data Analytics

Our literature search turned up very few academic articles in the field of business and management that focuses explicitly on how government policies may enhance or inhibit big data analytics. The synthesis presented here is based on these articles and complemented with practitioner-oriented publications.

In assessing the link between government and big data analytics, Jin et al. (2015) highlighted several important applications. These authors noted that at the national level, the capacity to accumulate, process, and utilize vast amounts of data will become a new landmark of a country's strength and competitiveness. In this regard, it seems that close cooperation and collaboration between governments, industry and universities to develop tools, technologies, and talent to work with and explore big data will be crucial. From a Canadian perspective, it seems that extending the Government of Canada Open Government initiative could result in greater access to hordes of government data, which firms and entrepreneurs could utilize to promote socio-economic development. Indeed, there are numerous examples around the world where government data has been utilized to achieve social goals such as public health, better service delivery, and more efficient government. These include smart cities, smart health, and smart grid projects where services are provided to optimize delivery, cost, efficiency, and effectiveness. Analyzing and mining government big data could also help to safeguard public security, combat criminal activities, and prevent economic crimes (Jin et al., 2015).

Apart from utilizing government data to improve government service delivery and make government more efficient, Jin et al. (2015) noted that the data sovereignty of a country in cyberspace will be another great power-game space in addition to land, sea, air, and outer spaces. Essentially, it will be another economic and strategic resource that can affect a country's sovereignty, security, competitiveness and prosperity. In this regard, several countries including China, the United States, France, the United Kingdom, Germany, and Canada are actively pursuing big data initiatives.

Generally, governments face several challenges in opening its massive data to the public despite the huge potential socio-economic benefits. The first surrounds issues of privacy, security, and harm caused by misuse whether unintended or not. This issue has been addressed by experts in this field (e.g., Judge & Pal, 2016 SSHRC Synthesis Report) and will not be addressed here except to say that a balanced legal framework that allows for appropriate use may be helpful. The second challenge pertains to cooperation and collaboration among the various government departments and agencies to make their data available. This may involve rethinking some of the regulatory and logistical barriers to effective sharing. Also, the engagement of the country's leading research and scientific agencies that have very sophisticated knowledge, skills and capabilities through the creation of a big data ecosystem could accelerate the Open Government initiative. The third challenge relates to the readiness of the public service in terms of their knowledge, skills, and capabilities, to serve and engage with big data analytics organizations and the public. Similar to the private industry, a public service that is lacking the appropriate levels and types of big data analytics skills, a data-driven culture, and associated data governance structure may be unable to effectively serve the private sector and citizens in a data-intensive world. Empirical evidence of the state of big data readiness of the Government of Canada and its provincial and municipal counterparts are virtually nonexistent. The appointment of a Chief Data Officer or a Chief Data Scientist to oversee and coordinate the government big data initiatives could help accelerate progress.

FUTURE RESEARCH

This synthesis reveals many areas and topics for future big data analytics research. Some of these include: (1) Big data analytics challenges for Canadian companies, particularly since the adoption rate is dismally low; (2) Skills, talents, and capabilities for the future workforce in light of the increasing use of computers and algorithms to replace not only routine tasks but managerial functions and complex tasks; (3) Collaboration approaches among industry, government and universities to deliver academic and on-the-job training to ensure talent pools are equipped with the right skills to support the ever-changing big data analytics environment; (4) Empirical research on the value of big data analytics initiatives that can help managers better deploy and harness the value creation potential of their big data initiatives; and (5) Understanding how organizations can develop a culture that embraces data-driven decision-making across all levels and ranks.

CONCLUSION

In this report, we synthesize the academic management and business literature on big data analytics. We focused on five interrelated themes to determine the state of knowledge, and possible gaps, regarding the key factors that facilitate or inhibit an organization's ability to harness the value of big data. The themes are the prerequisites for successful deployment of big data analytics; the mix of knowledge, skills and capabilities for careers in big data analytics; the application of big data analytics for creativity, innovation, and value creation; the challenges in harnessing value from big data initiatives; and the role of government policies in advancing big data analytics in the economy. We observe that while there are many players (technology vendors, consulting companies, academics, universities and colleges, governments, and others) that are actively promoting big data analytics, adoption by firms, governments and other organizations remains at very low levels. Many companies are uncertain as to how to embed big data analytics into their businesses while others are struggling to harness the value from their big data initiatives. We found that the path from big data to big impact is littered with both technical and managerial/organizational challenges. It seems that managerial and organizational challenges are much more difficult to overcome than technical challenges. Companies that were considered successful in realizing value from their big data initiatives had embedded a data-driven decision-making culture in their organizations i.e. decisions at all levels in the organization from senior managers to frontline workers make decisions based on data rather than intuition or past practices. Additionally, we observe that there is a lack of clear understanding of the precise knowledge, skills and capabilities people should have to work in order to work in a big data environment. However, a strong case has been made that the skill needed are different and workers must have some level of proficiency in business, analytical, and technical skills in order to understand each other in a big data environment. The skills issue also has another dimension to it as computers and algorithms are increasingly replacing routine tasks as well as managerial functions and even complex tasks. This may lead to some level of deskilling of some people. Finally, we observe that big data analytics have generated numerous innovations and have been used in many contexts to provide socio-economic benefits. Despite this there are many areas of big data analytics where we know very little. One such example pertains to the challenges Canadian SMEs face in adopting big data. Academic research in this regard is very thin.

KNOWLEDGE MOBILIZATION

Our knowledge mobilization plan for the remaining term of the grant will involve presentation of our report findings to both academic and practitioner audiences. The results will be disseminated through two seminars, one in Ottawa and one in Toronto. We anticipate that both seminars will involve about 50 participants and will comprise of academics, policymakers, and practitioners. The seminar in Ottawa will be held at the Telfer School of Management. We will utilize the Telfer School's research seminar series infrastructure and mailing list for this event. The venue of the Toronto seminar is to be determined. Summary results in the form of key highlights, written in practitioner-oriented format, will be posted on the Telfer School's website and other portals such as Researchgate.

To further disseminate our findings to both Canadian and international audiences, we plan to present the findings at both the Administrative Sciences Association of Canada (ASAC) conference and another international management conference on big data analytics such as the Academy of Management. We will also prepare a literature review paper to submit for publication to either a management journal or big data analytics journal.

We have already seized the opportunity to present our findings in an international event in Cali, Columbia, hosted by Pontificia Universidad Javeriana in mid-October. There were about 60 participants comprising of academics, graduate students, and representatives of the private sector.

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