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Emergence of Big Data Research in Operations Management, Information Systems, and Healthcare: Past Contributions and Future Roadmap

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In this day, in the age of big data, consumers leave an easily traceable digital footprint whenever they visit a website online. Firms are interested in capturing the digital footprints of their consumers to *understand and predict* consumer behavior. This study deals with how big data analytics has been used in the domains of information systems, operations management, and healthcare . We also discuss the future potential of big data applications in these domains (especially in the areas of cloud computing, Internet of Things and smart city, predictive manufacturing and 3-D printing, and smart healthcare) and the associated challenges. In this study, we present a framework for applications of big data in these domains with the goal of providing some interesting directions for future research.

Key words: big data; information systems; operations management; healthcare
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Data is the new science. Big Data holds the answers

—Pat Gelsinger (Gelsinger 2012)

1. Introduction

This is an era where we are generating data at an exponential rate. Large quantities of data representing our digital footprint are generated whenever we interact over social media and chat applications, use online shopping portals, or even when we use such ubiquitous applications as Google Search or Google Maps (Marr 2017a). Aside from data generated by us as users, an enormous amount of data comes from "smart" devices, that is, devices with sensors that collect data from the physical world and convert them into a digital form (Hashem et al. 2016, Riggins and Wamba 2015). This ever-growing stream of data generation is made possible by the advancements in computing and mobile technology and the increasing accessibility of the Internet. For example, according to a report by the United States Census Bureau, in 2015, 78% of U.S. households had a desktop or laptop, 75% had a handheld computer such as a smartphone, and 77% had a broadband Internet connection (Ryan and Lewis 2017). All of these devices, when connected to the Internet, have the ability to generate data in large quantities for those who know how to aggregate it.

It is these data—texts, reviews, ratings, news, images, videos, audio, email, chat communications, search history, etc.—that form the foundation of big data. Big data is characterized by four dimensions: *Volume*, *Velocity*, *Variety*, and *Veracity* (Dykes 2017, McAfee et al. 2012, Zikopoulos and Eaton 2011). Since the data is in unstructured form, a few years ago, it was almost impossible to analyze the data in this form and get meaningful insights. However, today with betterment of analytics tools and technology, not only can we obtain valuable information from the data but also use the insights to predict future trends (Chen et al. 2012). Most of the analytics involve artificial intelligence and machine learning (Marr 2017b). The computers are trained to identify patterns from the data and they can spot patterns much more reliably and efficiently than humans. Advanced analytics tools can produce millions of these results in a very short time. A report by Rubinson Partners, a marketing and research firm, shows that advertisers can boost their *Return on Advertisement Spending* (ROAS) by up to 16× using aggregated big data which give them information about the right time of advertising to the consumer (Rubinson 2017).

As a result, there is tremendous curiosity about the application of big data among corporate houses. Anyone who wants to have or maintain leverage over their competitors today is encouraged to gather data and analyze them using big data analytics. However, there is still a lack of knowledge about how to implement big data analytics in many companies. In this article, we investigate how several disciplines, specifically Information systems, operations and supply chain management, and healthcare, have applied big data in their domain. We also explore future research avenues for big data in these areas.

2. Information Systems

There was a time in academic research when data were collected solely for testing hypotheses to confirm our belief about certain phenomena or behaviors. However, when we use the Internet today, we leave a digital footprint that can be easily traced, collected, and utilized by big data analytics to *understand and predict* consumer behavior. Today it is even possible to store and analyze such massive data at an inexpensive rate. These analytics technologies can deliver new knowledge on their own without active human intervention (Dhar 2013), and as such can be very valuable.

Information systems (IS) has been an interdisciplinary domain conducting research at the intersection of computer technology and data from the business world (Agarwal and Dhar 2014). A majority of the existing research in the IS domain focuses on understanding and implementing processes that increase the efficiency of business operations. Since IS researchers were accustomed to handling huge volume of data, they started with an early advantage as far as research in big data is concerned, when compared to other business disciplines (Goes 2014). IS has contributed to the field of work surrounding big data in many ways, including surrounding issues of data integrity, data security and cybersecurity, social media, e-commerce, and web/mobile advertising. We briefly discuss the recent work in each of these areas.

Data integrity is critical to big data. To semantically integrate heterogeneous databases, it is essential to identify what entities in a data source map to the same entities in some other data sources so that data have a uniform and common structure across all heterogeneous databases (Kong et al. 2016). This process is called *entity reconciliation* (Enríquez et al. 2017, Zhao and Ram 2005). Entity reconciliation is of paramount importance to the process of data integration and management in the big data environment. Researchers have studied entity reconciliation from various perspectives. For example, Li et al. (2011) propose a context-based entity description (CED) for entity reconciliation where objects can be compared with the CED to ascertain their corresponding entities. Some researchers have also studied rule-based frameworks for entity reconciliation (Li et al. 2015).

Data security is another topic in big data where several research studies have been conducted (e.g., Chen and Zhang 2014, Demchenko et al. 2013, Katal et al. 2013). Some studies suggest the use of *real-time security analysis* as a measure for risk prevention (Lafuente 2015), whereas some others investigate *privacy-preserving data mining* (PPDM) operations (Xu et al. 2014). PPDM is a method of preserving data in such a way that applying data mining algorithms on the data do not disclose any sensitive information about the data. Big data analytics and optimization can be used as an answer against advanced cybersecurity threats (Ji et al. 2016). Since big data covers massive breadth of information sources and enormous depth of data, specifying and detecting risks become very precise (Hurst et al. 2014, Sagiroglu and Sinanc 2013).

Some work at the interface of IS-Marketing research has also touched on the topic of big data. For example, data from social media have been analyzed to comprehend behavior and predict events (Ruths and Pfeffer 2014, Xu et al. 2017). In this direction, Qiu and Kumar (2017) study the performance of prediction markets through a randomized field experiment and find that an increase in audience size and a higher level of online endorsement lead to more precise predictions. Moreover, they also suggest integrating social media in predicting market because social effects and reputational concerns improve the participants' prediction accuracy. The results from this study recommend that the predictions will be more refined by targeting people of intermediate abilities. Another area of social media research where big data has contributed is text analysis and sentiment mining (Mallipeddi et al. 2017, Salehan and Kim 2016). In this area, Kumar et al. (2018a) study the importance of management responses to online consumer reviews. The results show that organizations who chose to respond to consumer comments and reviews experienced a surge in the total number of check-ins. Findings from this study also confirm that the spillover effect of online management response on neighboring organizations depends on whether the focal organization and the neighboring organizations are direct competitor of each other. Furthermore, Millham and Thakur (2016) examine the pitfalls of applying big data techniques to social media data. In this direction, Kumar et al. (2018b) propose a novel hierarchical supervised-learning approach to increase the likelihood of detecting anomalies in online reviews by analyzing several user features and then characterizing their collective behavior in a unified manner. The dishonest online reviews are difficult to detect because of complex interactions between several user characteristics, such as review velocity, volume, and variety. Kumar et al. (2018b) model user characteristics and interactions among them as univariate and multivariate distributions. They then stack these distributions using several supervised-learning techniques, such as Logistic Regression, Support

Vector Machine, and k-Nearest Neighbors yielding robust meta-classifiers.

Big data analytics has also been studied from the point of view of strategic decision-making in e-commerce (Akter and Wamba 2016) and digital marketing (Fulgoni 2013, Minelli et al. 2012). Some of the growing areas of research in e-commerce include the advertising strategy of online firms and their use of recommender systems (Ghoshal et al. 2014, 2015, Liu et al. 2012). For example, Liu et al. (2012) study the advertising game between two electronic retailers subject to a given level of information technology (IT) capacity. They reach the conclusion that if IT capacity constraints of the firms are not included in advertisement decisions, then it may result in wastage of advertisement expenditure. Based on their results, they present implementable insights for policy makers regarding how to control wasteful advertising. Ghoshal et al. (2015) find that recommendation systems impact the prices of products in both personalizing and non-personalizing firms.

Furthermore, web and mobile advertising has been an interesting area of research since the arrival of dot-com firms (Dawande et al. 2003, 2005, Fan et al. 2007, Kumar and Sethi 2009, Kumar et al. 2006). Dutta et al. (2017) and Kumar (2015) summarize the use and future trends of data analytics and optimization in web and mobile advertising. Mookerjee et al. (2016) develop a model predicting visitor's click on web advertisements. They then discuss an approach to manage Internet ads so that both click-rate and revenue earned from clicks are increased. The above group of scholars has also developed a decision-model that maximizes the advertising firm's revenue subject to a click-through rate constraint (Mookerjee et al. 2012, 2016). Another study uses the real-world data to validate new optimization methods for mobile advertising (Mookerjee et al. 2014).

IS scholars have also studied big data as a service, for example, a platform combining big data and analytics in cloud computing (Assunção et al. 2015, Demirkan and Delen 2013, Zheng et al. 2013). For instance, the Big-Data-as-a-Service (BDaaS) has been explored to yield user-friendly application programming interfaces (APIs) so that the users can easily access the service-generated big data analytic tools and corresponding results (Zheng et al. 2013). Cloud computing plays a vital role in the use and adaption of big data analytics because infrastructure requirement and cost of resources can be adjusted according to actual demand (Assunção et al. 2015).

Some studies have also been conducted on IT governance from the perspective of big data (Hashem et al. 2015, Tallon 2013) and deception detection (Fuller et al. 2013, Rubin and Lukoianova 2015). In the IT governance domain, Tallon (2013) suggests that good data governance practices maintain a balance between value creation and risk exposure. Implementing such practices help firm earn a competitive leverage from their use of big data and application of big data analytics.

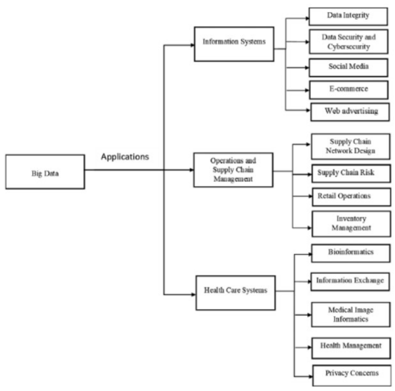
Figure 1 summarizes the above discussion. This figure also includes the contributions of big data in Operations and Supply Chain Management, and Healthcare (discussed in the following sections).

3. Operations and Supply Chain Management

With the betterment of *enterprise resource planning* (ERP) software, it is easier to capture data at different levels of operations. Firms want to analyze these data to develop more efficient processes. Hence, big data and big data analytics are being used by operations and supply chain academia as well as the industry to get insights from existing data in order to make better and informed decisions (Muhtaroglu et al. 2013, Wamba et al. 2015). The key areas in this domain where big data has left an impact are supply chain network design, risk management, inventory management, and retail operations.

Big data analytics has been used to align sourcing strategies with the organizational goals (Romano and Formentini 2012) and to evaluate the performance of suppliers (Chai and Ngai 2015, Choi 2013). Supply chain network design can itself account for a massive amount of data and hence is a favorite area for

Figure 1 Summary of Big Data Research in Operations Management, Information Systems, and Healthcare



applying big data analytics. Researchers have studied supply chain network design where the demand is uncertain (Benyoucef et al. 2013, Bouzembrak et al. 2012, Soleimani et al. 2014) as well as where the demand is certain (Jindal and Sangwan 2014, Tiwari et al. 2012). Firms can use analytics to ascertain the cost, quality, and time-to-market parameters of products to gain leverage over competitors (Bloch 2011, Luchs and Swan 2011, Srinivasan et al. 2012).

Big data analytics has also been applied to maximize production (Noyes et al., 2014) and minimize the material waste (Sharma and Agrawal 2012). Noyes et al. (2014) recommend that changes in existing manufacturing processes, incorporating automation, and simplification of methods and raw materials, will result in increasing the speed and throughput of in-process analytics during polysaccharide manufacturing processes. Moreover, Sharma and Agrawal (2012) implemented fuzzy analytic hierarchy process to solve production control policy selection problem. Inventory challenges, such as cost, demand, and supply fluctuations have also been studied using big data analytics (Babai et al. 2009, Hayya et al. 2006). In this direction, Babai et al. (2009) discuss a new dynamic inventory control method where forecasts and uncertainties related to forecast are exogenous and known at each period.

Big data has also been increasingly used in retailing. In the last decade, retailing has been one of the key areas of research for the OM researchers, especially with the growth of multi-channel retailing (Mehra et al. 2018). Big data analytics has also been applied to retail operations by firms to reduce cost and to market themselves better than the competition (Dutta et al. 2017, Janakiraman et al. 2013, Kumar et al. 2017). For instance, big data techniques are now being heavily used in recommender systems that reduce consumer search efforts (Dutta et al. 2017). Kumar et al. (2017) study how the presence of brick-and-mortar stores impacts consumers' online purchase decision. Furthermore, Janakiraman et al. (2013) study product returns in multi-channel retailing taking into consideration consumers' channel preference and choice.

4. Healthcare Systems

Healthcare systems in the United States have been rapidly adopting electronic health records (EHRs) and Healthcare Information Exchanges (HIEs) that are contributing to the accumulation of massive quantities of heterogeneous medical data from various sections of the healthcare industry—payers, providers, and pharmaceuticals (Demirezen et al. 2016, Rajapakshe et al. 2018). These data can be analyzed in order to derive insights that can improve quality of healthcare (Groves et al. 2016). However, the analyses and practical applications of such data become a challenge because of its enormity and complexity. Since big data can deal with massive data volume and variety at high velocity, it has the potential to create significant value in healthcare by improving outcomes while lowering costs (Roski et al. 2014). It has been shown to improve the quality of care, make operational processes more efficient, predict and plan responses to disease epidemics, and optimize healthcare spending at all levels (Nambiar et al. 2013). Here, we explore how big data analytics has revolutionized the healthcare industry.

4.1. Bioinformatics

One of the subsections of the healthcare industry where big data has contributed the most is biomedical research. With the emergence and enhancement of parallel computing and cloud computing—two of the most important infrastructural pillars of big data analytics—and with the extensive use of EHRs and HIEs, the cost and effort of capturing and exploring biomedical data are decreasing.

In bioinformatics, big data contributes in yielding infrastructure for computing and data processing, including error detection techniques. Cloud-based analytics tools, such as Hadoop and MapReduce, are extensively used in the biomedical domain (Taylor 2010). Parallel computing models, such as CloudBurst (Schatz 2009), Contrail (Schatz et al. 2010), and Crossbow (Gurtowski et al. 2012), are making the genome mapping process easier. CloudBurst improves the performance of the genome mapping process as well as reduces the time required for mapping significantly (Schatz 2009). DistMap, a scalable, integrated workflow on a Hadoop cluster, supports nine different mapping tools (Pandey and Schlötterer 2013). SeqWare (D O'Connor et al. 2010), based on Apache HBase database (George 2011), is used for accessing large-scale whole-genome datasets, whereas Hydra (based on Hadoop-distributed computing framework) is used for processing large peptide and spectra databases (Lewis et al. 2012). Tools such as SAMQA (Robinson et al. 2011), ART (Huang et al. 2011), and CloudRS (Chen et al. 2013a) help in identifying errors in sequencing data. Furthermore, *Genome Analysis Toolkit* (GATK) (McKenna et al. 2010, Van der Auwera et al. 2013), BlueSNP (Huang et al. 2012), and Myrna (Langmead et al. 2010) are toolkits and packages that aid researchers in analyzing genomic data.

4.2. Healthcare Information Exchange

Clinical informatics focuses on the application of IT in the healthcare domain. It includes activity-based research, analysis of the relationship between a patient's main diagnosis (MD) and underlying cause of death (UCD), and storage of data from EHRs and HIEs (Luo et al. 2016). Big data's main contributions have been to the manner in which EHR and HIE data are stored. The clinical real-time stream data are stored using NoSQL database, Hadoop, and HBase database because of their high-performance characteristics (Dutta et al. 2011, Jin et al. 2011, Mazurek 2014). Some research work has also studied and proposed several interactive methods of sharing medical data from multiple platforms (Chen et al. 2013b).

Healthcare Information Exchanges are used for efficient information sharing among heterogeneous healthcare entities, thus increasing the quality of care provided. Janakiraman et al. (2017) study the use of HIEs in emergency departments (EDs) and find that the benefits of HIEs increase with more information on patients, doctors, and prior interaction between them. Yaraghi et al. (2014) model HIE as a multi-sided platform. Users evaluate the self-service technologies of the model based on both user-specific and network-specific factors. Another body of research studies whether healthcare reforming models leads to better patient-centric outcomes (Youn et al. 2016).

Big data techniques have enabled the availability and analyses of a massive volume of clinical data. Insights derived from this data analysis can help medical professionals in identifying disease symptoms and predicting the cause and occurrence of diseases much better, eventually resulting in an overall improved quality of care (Genta and Sonnenberg 2014, McGregor 2013, Wang and Krishnan 2014). Since the size and complexity of data are enormous and often involve integrating clinical data from various platforms to understand the bigger picture, data security is often compromised during analysis of clinical data. Big data techniques can address this issue (Schultz 2013). Researchers have proposed several models and frameworks to efficiently protect the privacy of the data as well as effectively deal with concurrent analyses of datasets (Lin et al. 2015, Sobhy et al. 2012).

4.3. Medical Image Informatics

With the dawn of improved imaging technology, EHRs are often accompanied with high quality medical images. Studying the clinical data along with the analysis of such images will lead to better diagnoses, as well as more accurate prediction of diseases in future (Ghani et al. 2014). Medical image informatics focuses on processing images for meaningful insights using big data tools and technologies. Similarly, picture archiving and communication systems (PACS) have been critically advantageous for the medical community, since these medical images can be used for improved decision regarding treatment of patients and predicting re-admission (Ghani et al. 2014). Silva et al. (2012) discuss how to integrate data in PACS when the digital imaging and communications in medicine (DICOM) object repository and database system of PACS are transferred to the cloud. Since analyzing large quantities of high quality clinical images using big data analytics generates rich, spatially oriented information at the cellular and sub-cellular levels, systems such as Hadoop-GIS (Wang et al. 2011), that is, cost-effective parallel systems, are being developed to aid in managing advanced spatial queries.

4.4. Health Management

Recent studies have also used big data techniques to analyze the contents of social media as a means for contagious disease surveillance, as well as for monitoring the occurrence of diseases throughout the world (Hay et al. 2013, Young et al. 2014). Big data analytics tools are used on social media communications to detect depression-related emotional patterns, and thus identify individuals suffering from depression from among the users (Nambisan et al. 2015). Health IT infrastructures, such as the US Veterans Health Administration's (VHA), have facilitated improved quality of care by providing structured clinical data from EHRs as well as unstructured data such as physician's notes (Kupersmith et al. 2007).

4.5. Privacy Concerns

In coming times, there is a massive potential of HIEs becoming public utility infomediaries that many interested markets can access to derive information (De Brantes et al. 2007). However, a major hurdle that adaption of HIEs faces is privacy concern among consumers. A section of researchers is building HIE frameworks incorporating privacy and security principles. For example, Pickard and Swan (2014) have created a health information sharing framework, which increases sharing of health information, built on trust, motivation, and informed consent. Trust is necessary for dealing with access control issues, motivation maps the willingness to share, and informed consent enforces the legal requirement to keep the information safe. In another study, Anderson and Agarwal (2011) find that type of the requesting stakeholder and how the information will be used are two important factors that affect the privacy concern of an individual while providing access to one's health information. Numerous states in the United States have enacted laws that incentivize HIE efforts and address the concerns of patients regarding sharing of health information. In another study, Adjerid et al. (2015) observe whether various forms of privacy regulation policies facilitate or decrease HIE efforts. They find that although privacy regulation alone negatively effects HIE efforts, when combined with incentives, privacy regulation with patient consent requirement positively impacts HIE efforts.

5. Way Ahead: Potential Applications and Challenges

In this section, we discuss the potential of big data applications in Information Systems, Operations/Supply Chain, and Healthcare domains. Figure 2 summarizes the key areas of future research.

5.1. Internet of Things (IoT) and Smart City

The Internet of Things creates a world of interconnected sensory devices containing sensors that can collect and store information from their respective real-world surroundings (Hashem et al. 2016, Riggins and Wamba 2015). According to Business Insider, the number of IoT devices will be 75 billion by the year 2020 (Danova 2013). These devices can be sensors, databases, Bluetooth devices, global positioning system (GPS), and radio-frequency identification (RFID) tags (O'Leary 2013). These devices collect massive amount of data, and if we delve down deep into this information using big data analytic tools and techniques, we may be able to derive useful insights. The applications of IoT and big data analytics combined have the potential to bring path-breaking changes to various industries and academic research. However, at the same time, since these subjects are still very new, there are uncertainties among scholars about how to implement them, and how best to extract the business value from these concepts (Riggins and Wamba 2015).

One of the domains where the coupling of big data techniques and IoT has made significant progress is the concept of a smart city, that is, where each component of urban surrounding consists of devices that are connected to a network (Hashem et al. 2015). These devices can collect data from their surroundings and share among themselves. These data can be used to monitor and manage the city in a refined dynamic manner, to improve the standard of living, and to also support the sustainability of the smart city (Kitchin 2014). IoT concepts enable information sharing across various devices, thus aiding in the creation big data caches. Furthermore, big data analytics are used to conduct real-time analysis of smart city components. Kitchin (2014) mentions that urban governance decisions and future policies regarding city life are based on these analyses. Some sub-areas under smart city where the bulk of research is being conducted are energy grids (Chourabi et al. 2012), smart environments (Atzori et al. 2010, Nam and Pardo 2011, Tiwari et al. 2011), waste management (Neirotti et al. 2014, Washburn et al. 2009), smart healthcare (Nam and Pardo 2011, Washburn et al. 2009), and public security (Neirotti et al. 2014, Washburn et al. 2009). An emerging field surrounding smart city research is an area where big data has the potential to make a lot of contribution in the coming days.

5.2. Predictive Manufacturing and 3-D Printer

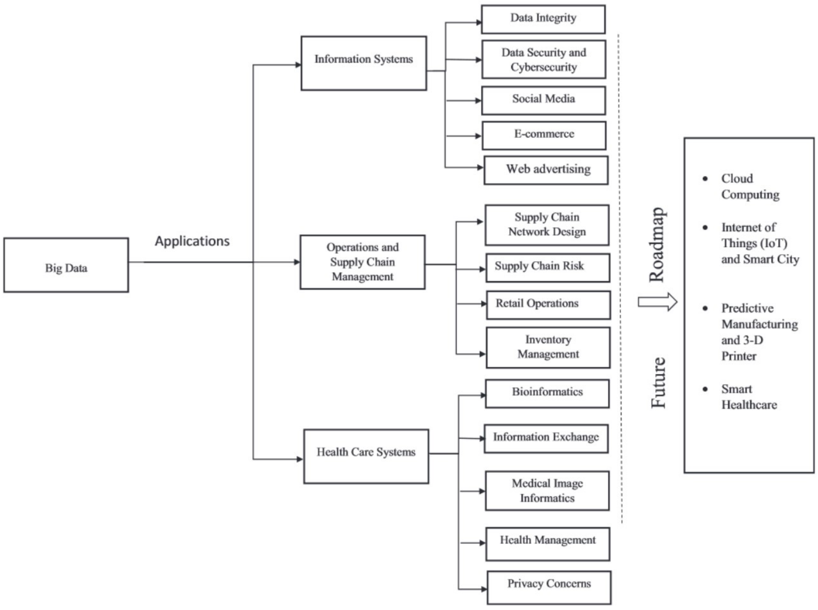
Predictive manufacturing is based on cyber physical systems (CPS). CPS consists of devices that communicate with each other, as well as with the physical world, with the help of sensors and actuators (Alur 2015). CPS technology is becoming increasingly popular among manufacturers in the United States and Europe as it allows them to gain an edge in international manufacturing dynamics (Wright 2014). CPS technology can also be used to improve the design of products, to track its production and in-service performance, and to enhance productivity and efficiency of the manufacturers. General Electric (GE) and Rolls Royce have embedded sensors on their jet engines that capture data during flight and post-flight, and maintenance decisions can then be made based on these logged data (Dai et al. 2012).

Massive amounts of data are being collected from manufacturing plants through RFID and CPS technologies (Lee et al. 2013). As more advancement is made in big data analytics, these data about production equipment and operations can be processed better. Security of CPS and predictive manufacturing is another potential area where big data techniques can be applied for better security outcomes. Furthermore, additive manufacturing processes, also known as 3-D printing, are used to build three-dimensional objects by depositing materials layer-by-layer (Campbell et al. 2011, Conner et al. 2014). 3-D printing is a path-breaking technology that, in coming future, will make the existing models of manufacturing for certain products obsolete (Waller and Fawcett 2013). Hence, it is profoundly important that we study the applications of big data analytics to additive manufacturing in order to derive insights.

5.3. Smart Healthcare

Smart Healthcare is an extension of IoT ideas in the healthcare industry; that is, IoT devices equipped with RFID, Wireless Sensor Network (WSN), and advanced mobile technologies are being used to monitor patients and biomedical devices (Catarinucci et al. 2015). In the smart healthcare architecture, IoT-supporting devices are being used for seamless and constant data collection, and big data technology on the cloud is being used for storing, analyzing, and sharing this information (Muhammad et al. 2017). The nexus of IoT and big data analytics hosted on

Figure 2 Possible Future Research Directions for Big Data Applications in Operations Management, Information Systems, and Healthcare



cloud technology will not only help in more accurate detection and treatment of illnesses, but will also provide quality healthcare at a reduced cost (Varshney and Chang 2016). Moreover, smart healthcare enables to bring specialized healthcare to people who have restricted movement, or who are in remote areas where there is a dearth of specialized doctors (Muhammad et al. 2017).

Recently, the use of wearable devices has seen a rapid growth, and the number of such units shipped annually is expected to reach 148 million by 2019 (Danova 2015). Olshansky et al. (2016) discuss how data captured by wearable devices can be transmitted to health data aggregation services, such as Human API (humanapi.co) and Welltok (welltok.com), who can transform the data into measures of risk. These measures can be used to observe health trends as well as to detect and prevent diseases. Some promising topics of research in the smart healthcare domain where big data can play an important role are smart and connected health (Carroll 2016, Harwood et al. 2014, Leroy et al. 2014), and privacy issues in the smart healthcare framework (Ding et al. 2016).

6. Fading Boundaries

In this article, we explored the application of big data in three different domains—information systems, operations and supply chain, and healthcare. But, the line between these disciplines are blurring with each passing day. Several new avenues of research are becoming popular that are common to at least two of these domains. One such topic is use of ERP platforms in healthcare that is common to all the three fields.

Healthcare organizations accumulate massive amounts of information from various departments and then different entities in healthcare management rely on to carry out their services. An automated integrated system, such as an ERP system to manage the information coming from different services and processes, will enable healthcare organizations to improve efficiency of service and quality of care

(Handayani et al. 2013). The motivations underlying the adoption of ERP system in healthcare management are technological, managerial, clinical, and financial (Poba-Nzaou et al. 2014). An ERP system integrates various business units of healthcare organization, such as finance, operation and supply chain management, and human resource, and provides easy access within each unit. It can also address the disparity in healthcare quality between urban and rural settings. ERP provides connectivity among all healthcare centers and hence information can also be accessed from rural centers (Padhy et al. 2012). Benefits from implementing ERP can be classified into four categories—patients' satisfaction, stakeholders' satisfaction, operations efficiency, and strategic and performance management (Chiarini et al. 2017). However, ERP systems are costly to acquire and involve hidden costs even after successful implementation such as integration testing and staff members training costs (Gupta 2000, Wailgum 2008). Till date, majority of research work involving ERP in healthcare domain has revolved around implementation of ERP systems (Mucheleka and Halonen 2015). One potential research avenue is to conduct empirical studies to quantify the benefits from implementation of such systems.

7. Closing Thoughts

We generate data whenever we use the Internet. Aside from the data generated by us, several interconnected smart devices collect data, that is, devices with sensors collect data from their surrounding real world. With this tremendous quantity of data generated each day, big data and big data analytics are very much in demand in several industries as well as among scholars. In this study, we discussed the contributions of big data in information systems, operations and supply chain management, and healthcare domains. At the end, we talked about four sub-areas of these domains—cloud computing, Internet of things (IoT) and smart city, predictive manufacturing and 3-D printer, and smart healthcare—where big data techniques can lead to significant improvements. We also discussed the corresponding challenges and future research opportunities in the field, noting numerous areas for growth and exploration.

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