



Effective Decision Support in the Big Data Era: Optimize Organizational Performance via BI&A

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ABSTRACT

This study conducts a review and synthesis of the business intelligence and analytics (BI&A) evolution, applications, frameworks, and emerging trends with the aim to provide a summary of core concepts, a succinct but valuable description of main applications and frameworks, and an account of main recommendations for addressing the big data challenges and opportunities. It develops an integrated and organized view on the BI&A evolution process and presents an integrated BI&A application framework to help organizations adopt or develop the appropriate BI&A solutions to derive the desired impact in the big data era. This paper also elicits a set of practical recommendations to executives and leaders in organizations worldwide for interpreting the BI&A literature and applying the rich body of knowledge for IT practitioners. It traces the BI&A evolution to data-driven discovery and highly proactive and creative decision-making utilizing advanced analytical techniques with unstructured and massive data sources to cope with a highly dynamic global business environment in the big data era.

KEYWORDS

Analytics, Big Data, Business Intelligence, Data-Centric Approach

1. INTRODUCTION

In the last 30 years, the tools and mechanisms for supporting organizational decision making have been intensively data driven (Chen et. al., 2012). More recently, the integration of data-inference mechanisms from statistics, machine learning, artificial intelligence, mathematics, optimization and databases have converged into a new dynamic business phenomenon (Kesavan & Kushwaha, 2020). An overwhelming amount of web-based, mobile, and sensor-generated data arrive at a terabyte and even exabyte scale and decision support information and insights can be obtained and derived from the highly detailed, contextualized, and rich contents of relevance to any business (Chen et. al., 2012; Mashingaidze & Backhouse, 2017; Ukhalkar et. al., 2020).

The term Big Data, accordingly, refers to data sets whose sizes are beyond the ability of common software tools to capture, curate, manage, process, analyze, and store within a specified elapsed time

DOI: 10.4018/IJDSST.286683

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(Abbasi et al, 2016). Recent studies show that a majority of employers in the market believe that their organization's need for Big Data skills and support tools will rise in the future (Bharadwaj et al., 2013; Wixom et al., 2013; Ukhalkar et. al., 2020). With the prominent value proposition, Big Data also brought big challenges for businesses and decision makers across all walks of life. More than often businesses are collecting more data than they know what to do with. Successful decision makers must be able to work with the data, make sense of it, and understand the big picture approach to using Big Data to gain insights (Willwhite, 2014; Asllani, 2015; Mashingaidze & Backhouse, 2017).

Due to Big Data, business executives and managers can measure, and hence know, radically more about their businesses, and directly translate that knowledge into improved decision making and performance (McAfee & Brynjolfsson, 2012; Hariri et. al., 2019). Modern business analytics has become their weapon of choice. Business Intelligence and Analytics (BI&A), for instance, have experienced significant growth over the past two decades and have been identified as one of the four major technology trends in the 2010s (IBM Tech Trends Report, 2011). Indeed, organizations have become more competitive through the use of business intelligence and modern analytics in this Big Data era (Asllani, 2015; Ukhalkar et. al., 2020). Motivated by the emerging opportunities and challenges as well as lack of practical transference of applying BI&A in the Big Data era, we conduct a selective review (Glass et al., 2004; Webster & Watson, 2002) on the BI&A evolution, applications, frameworks and emerging trends with the aim to provide a summary of core concepts, a succinct but valuable description of main applications and frameworks, and an account of main recommendations for addressing the Big Data challenges and opportunities. The results of this research can help BI&A researchers to count with an updated and integrative summarization of the evolution of the BI&A, and to executives and managers to count with a set of updated recommendations for coping with Big Data challenges and opportunities.

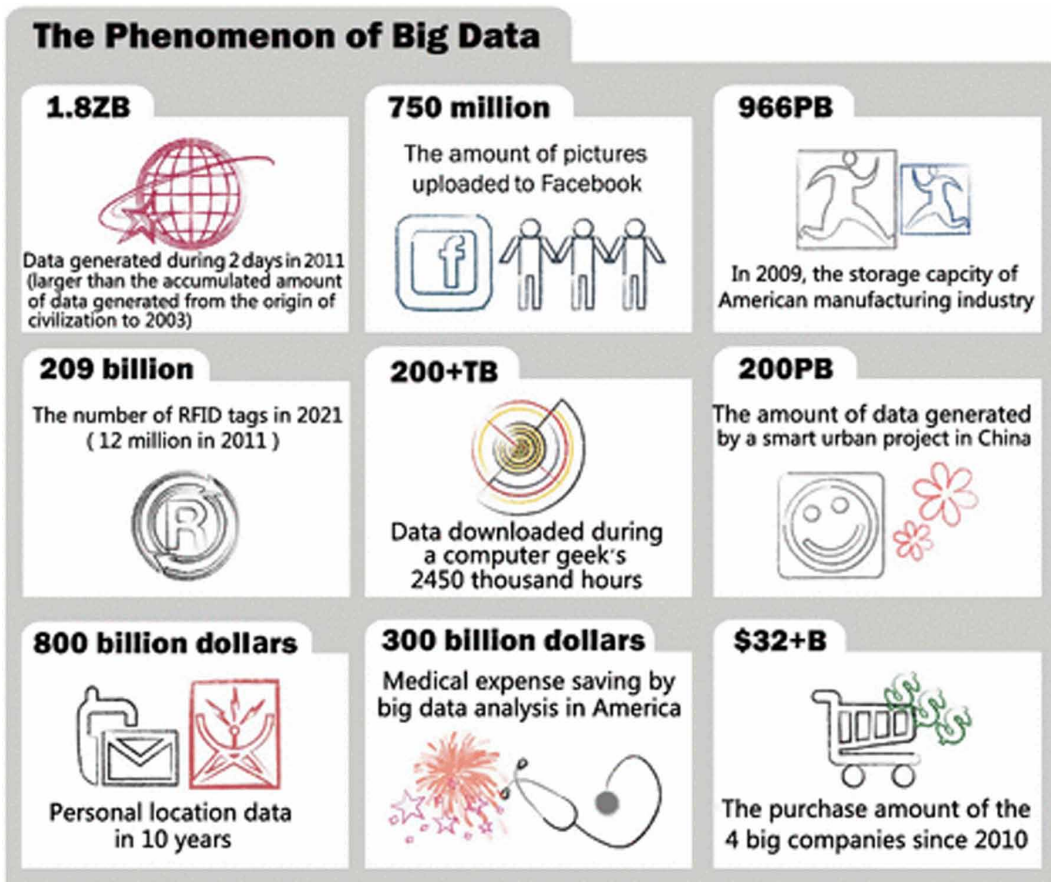
The remainder of this paper is structured as follows: a background overview of the Big Data challenges and opportunities for BI&A is depicted in section 2; the specification of the selective review research method as well as the research questions are explained in section 3; results and insights derived from the selective review are reported in section 4, including the BI&A evolution phases and their key characteristics from core studies, an investigation of BI&A applications and framework in the Big Data era, and a discussion of implications and insights for addressing the Big Data challenges for BI&A researchers and practitioners; and finally, in section 5, we conclude with the research limitations, recommendations, and conclusions.

2. BACKGROUND OVERVIEW: THE BIG DATA CHALLENGE & OPPORTUNITY

Modern businesses are now entering the new paradigm of Big Data. By 2022, 35% of large organizations will be either sellers or buyers of data via formal online data marketplaces, up from 25% in 2020. By 2023, graph technologies will facilitate rapid contextualization for decision making in 30% of organizations worldwide. Graph analytics is a set of analytic techniques that allows for the exploration of relationships between entities of interest such as organizations, people and transactions (Gartner, 2020). Figure 1 below illustrates the phenomenon of Big Data worldwide.

So, what is Big Data? Big Data is an abstract concept that refers to massive data sets having large, more varied and complex structure with the difficulties of storing, analyzing and visualizing for further processes or results (Sagiroglu& Sinanc, 2013). Although there are variations about the exact definition, Big Data is typically characterized by three Vs: volume, velocity, and variety. Volume refers to the large size of the data such as terabytes (TB), petabytes (PB), exabytes (EB), zettabytes (ZB), etc. The volume of Big Data is larger than the volume processed by conventional relational databases in legacy systems. Velocity means how frequently the data is generated and flows into an organization. Real-time or nearly real-time information makes it possible for a company to be much more agile than its competitors (McAfee & Brynjolfsson, 2012; Hariri et al., 2019). Accordingly, variety refers to the sources, types and formats of data. Different from structured data sets, Big data

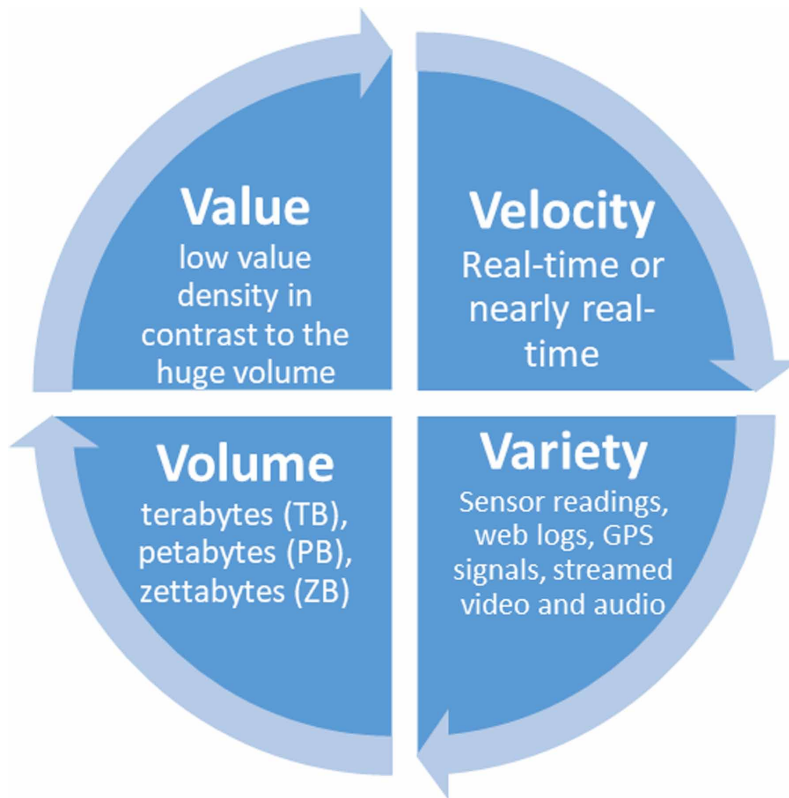
Figure 1. The boom of the global data volume (adapted from Chen et al., 2014)



takes a variety of forms ranging from RFID sensor readings, unstructured social networking messages and web logs, GPS signals from cell phones, streamed video and audio, and more. More recently, many researchers and practitioners proposed one additional key characteristic, namely, the 4th V of Big Data, value (Gantz & Reinsel, 2011; Hashem et al., 2015), which refers to the low value density in contrast to the huge volume of the large data set. It poses big challenges in discovering huge hidden values from large datasets with various types and rapid generation. Figure 2 below summarizes and depicts the four Vs of Big Data.

Processes, technologies, and products are intertwined. To evaluate and capitalize on their complementarity, scholars in each field will need to examine their assumptions, methods and questions and begin opening their conversations to one another (Mendling et al., 2020). One of the challenges in the era of Big Data is the increased difficulty of mining enormous amounts of data and information to identify the relevant pieces for effective decision making (Asllani, 2015). Wu et al. (2020) discuss the challenges of using cloud services and Big Data for sustainable development goals monitoring and to evaluate the impacts of policies, to ensure that the desired targets are achieved by 2030. The Big Data expansion, similar to the preceding analytics movement, seeks to glean intelligence from data and translate that into business competitiveness. However, to fully realize its potential, Big Data demands new techniques with many of these approaches still in the developmental stages. Asllani (2015) succinctly captures this transformation: “*acquiring the new tools requires a radical change in underlying beliefs or theory: they require a new way of thinking*” (pp. 6). Some of the inherited

Figure 2. The Four Vs Characteristics of Big Data



challenges in Big Data are finding capable ways to capture, store, analyze, and virtualize it in order to support more effective and efficient decision making. More specifically, the volume generally improves the quality and accuracy of BI&A models and solutions. Furthermore, according to Asllani (2015), robust BI&A models can accelerate the flow of information by offering quicker decisions and improving operational business intelligence. Variety, however, presents serious challenges in implementation of BI&A techniques for Big Data. With the right technological framework of the BI&A solution, the negative impact of variety can be mitigated (Asllani, 2015).

However, similar to many other technology innovations, Big Data's power does not eliminate the need for human insight or vision. In fact, the managerial challenges are greater than the technical challenges of using BI&A in the Big Data era and reaping the full benefits of the transition (McAfee & Brynjolfsson, 2012). Mikalef and Krogstie (2020) report that under different combinations of contextual factors the significance of Big Data analytics resources varies, with specific configurations leading to high levels of incremental and radical process innovation capabilities. Big data can be aligned with existing business intelligence tools that are used to provide intelligent aid for organizational processes (Dezi et al., 2018).

3. SELECTIVE REVIEW RESEARCH METHOD

The aim of this research is to develop an integrative selective review and synthesis of the Business Intelligence and Analytics (BI&A) concepts, evolution, frameworks, domains of applications, trends, and challenges in the context of Big Data for achieving effective decisional support. For this aim, we

establish the following specific research questions: RQ.1 What are the main concepts and evolution of Big Data BI&A aids? RQ.2 What are the most relevant Big Data BI&A framework's aids? RQ.3 What are the main domains of applications reported for Big Data BI&A aids? and RQ.4 What are the main trends and challenges for effective decisional support with Big Data BI&A aids?

To address these four research questions, we conducted a selective review of the scientific literature on the core topics of Big Data BI&A. A selective literature review is a descriptive and literature analysis research method (Glass et al., 2004) that addresses only a small sample of the most relevant studies on a topic of interest (Brereton et al., 2007). To achieve this selective literature review, we consider a worthy inclusion strategy to include relevant academic-oriented studies and high-quality professional literature for the 2000-2021 period. Business Intelligence started before the 2000 year and became relevant ever since, while Analytics and Big Data clearly emerged in the last 2010-2021 period. The inclusion criteria for academic-oriented documents were established as follows: C.1 type of document (journal article, research-oriented book, or conference paper); C.2 status of authors (well-recognized in the topics of Business Intelligence, and/or Analytics and/or Big Data); C.3 quality of publisher (document is published by a well-recognized international scientific editorial company), and C.4 citations (the document is highly cited OR the document was considered relevant despite a low number of citations). Accordingly, the inclusion criteria for high-quality professional literature were the following ones: C.1) type of document (textbook, industrial report, technical report, governmental studies, and blogs from professional societies; C.2) type of source (authors or the publishing organization are well-recognized in the topics of Business Intelligence, and/or Analytics and/or Big Data); and C.3) value of document (the document has been previously cited in relevant academic papers).

Tables 1 reports the list of the 22 selected papers in the period 2000-2021 on Business Intelligence, and/or Analytics and/or Big Data respectively from the academic and professional literature.

4. SELECTIVE REVIEW RESULTS AND SYNTHESIS

This section elicits the main findings related with the four identified research questions in the selected studies and elaborates an organized synthesis of the essential findings.

4.1 On Big Data BI&A Aids Concepts and Evolution

The term “intelligence” has been used by scholars in the field of artificial intelligence (AI) since the 1950s. Only three decades ago, “business intelligence” (BI) was recognized as a popular trend in the management information systems (MIS) field (Chaudhuri et al., 2011). Later with the advent and rapid advancement of Internet technologies, business analytics (BA) was introduced within the BI domain and simply defined as “using data for better decision making” (Watson & Wixom, 2007; Winston, 2013; Holsapple et al., 2014;). More recently, the rise of Internet of Things (IoT) or the Industrial Internet together with improved access to large amount of data is also fueling the Big Data trend (Zhao et al., 2014). The automation of business processes with information technology has led to the automatic capture of massive data (Liang & Liu, 2018). Accordingly, Big Data and Big Data analytics, considered in this paper as a sub-set of business analytics that offers new directions for BI&A, have been used to describe the unique and advanced analytical techniques that can handle the high volume, variety, value, and velocity of Big Data in business applications (Watson, 2013; Davenport, 2018; Sun et. al., 2018).

As a data centric approach that relies heavily on data collection, extraction, and analysis technologies, BI&A has its theoretical roots in the longstanding data management field (Davenport, 2006; Chen et. al., 2012; Davenport, 2013). According to Chen et al (2012), BI&A evolution process can be classified into phases 1.0 (DBMS-based), 2.0 (Web-based), and 3.0 (mobile and sensor-based). More specifically, BI&A 1.0 refers to the BI&A technologies and applications currently adopted in industry, where data are mostly structured, collected by companies through various legacy systems,

Table 1. List of the 22 Selected Studies on Big Data BI&A Aids

ID	INITIAL SET OF 4 DOCUMENTS LOCATED APPLYING THE QUERY IN THE SCHOLAR.GOOGLE.COM ACADEMIC SEARCH ENGINE	C.1 JOURNAL ARTICLE?	C.2 INDEX (JCR, SCOPUS)?	C.3 CITATIONS > 50?
1	Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. <i>MIS Quarterly</i> , 1165-1188.	YES	JCR	6075
2	Fan, S., Lau, R. Y., & Zhao, J. L. (2015). Demystifying big data analytics for business intelligence through the lens of marketing mix. <i>Big Data Research</i> , 2(1), 28-32.	YES	JCR	315
3	Liang, T. P., & Liu, Y. H. (2018). Research landscape of business intelligence and big data analytics: A bibliometrics study. <i>Expert Systems with Applications</i> , 111, 2-10.	YES	JCR	98
4	Sun, Z., Sun, L., & Strang, K. (2018). Big data analytics services for enhancing business intelligence. <i>Journal of Computer Information Systems</i> , 58(2), 162-169.	YES	JCR	93
	SET OF 7 RELEVANT DOCUMENTS CITED IN THE INITIAL SET OF 4 DOCUMENTS	C.1 JOURNAL ARTICLE	C.2 JOURNAL INDEX (JCR, SCOPUS)	C.3 CITATIONS > 50
5	Davenport, T. H. (2006). Competing on Analytics. <i>Harvard Business Review</i> , 84(1), 98-107.	YES	JCR	1513
6	Watson, H. J., & Witom, B. H. (2007). The current state of business intelligence. <i>Computer</i> , 40(9), 96-99.	YES	JCR	943
7	Chaudhuri, S., Dayal, U., & Narasayya, V. (2011). An overview of business intelligence technology. <i>Communications of the ACM</i> , 54(8), 88-98.	YES	JCR	1081
8	Tien, J. M. (2013). Big Data: Unleashing information. <i>Journal of Systems Science and Systems Engineering</i> , 22 (2), 127-151 .	YES	JCR	238
9	LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. <i>MIT Sloan management review</i> , 52(2), 21-32.	YES	JCR	1973
10	Delen, D., & Demirkan, H. (2013). Data, information and analytics as services. <i>Decision Support Systems</i> , 55(1), 359-363.	YES	JCR	395
11	Holsapple, C., Lee-Post, A., & Pakath, R. (2014). A unified foundation for business analytics. <i>Decision Support Systems</i> , 64, 130-141.	YES	JCR	362
	SET OF 11 NEW RELEVANT DOCUMENTS FROM AUTHORS IN THE INITIAL SET OF 4 DOCUMENTS OR THE SET OF 7 CITED DOCUMENTS	C.1 JOURNAL ARTICLE	C.2 JOURNAL INDEX (JCR, SCOPUS)	C.3 CITATIONS > 50
12	Lim, E. P., Chen, H., & Chen, G. (2013). Business intelligence and analytics: Research directions. <i>ACM Transactions on Management Information Systems (TMIS)</i> , 3(4), 1-10.	YES	JCR	191
13	Abhasi, A., Sarker, S., & Chiang, R. H. (2016). Big data research in information systems: Toward an inclusive research agenda. <i>Journal of the association for information systems</i> , 17(2), 3.	YES	JCR	610
14	Davenport, T. H. (2013). Analytics 3.0. <i>Harvard Business Review</i> , 91(12), 64-72.	YES	JCR	413
15	Davenport, T. H. (2018). From analytics to artificial intelligence. <i>Journal of Business Analytics</i> , 1(2), 73-80.	YES	JCR	73
16	Watson, H. J. (2019). Update tutorial: Big Data analytics: Concepts, technology, and applications. <i>Communications of the Association for Information Systems</i> , 44(1), 21.	YES	SCOPUS	34
17	Watson, H. J. (2013). All about analytics. <i>International Journal of Business Intelligence Research (IBIR)</i> , 4(1), 13-28.	YES	SCOPUS	32
18	Zhao, J. L., Fan, S., & Hu, D. (2014). Business challenges and research directions of management analytics in the big data era. <i>Journal of Management Analytics</i> , 1(3), 169-174.	YES	SCOPUS	48
19	Sun, Z., & Huo, Y. (2019). The spectrum of big data analytics. <i>Journal of Computer Information Systems</i> , 1-9.	YES	JCR	17
20	Sun, Z., Strang, K., & Firmin, S. (2017). Business analytics-based enterprise information systems. <i>Journal of Computer Information Systems</i> , 57(2), 169-178.	YES	JCR	79
21	Demirkan, H., & Delen, D. (2013). Leveraging the capabilities of service-oriented decision support systems: Putting analytics and big data in cloud. <i>Decision Support Systems</i> , 55(1), 412-421.	YES	JCR	670
22	Delen, D., & Ram, S. (2018). Research challenges and opportunities in business analytics. <i>Journal of Business Analytics</i> , 1(1), 2-12.	YES	SCOPUS	45

and often stored in commercial relational database management systems (RDBMS). In the 2000s, Web 2.0-based systems and analytical technologies have led to the exciting era of BI&A 2.0 research, which was centered on text and web analytics for unstructured web contents. Whereas web-based BI&A 2.0 has attracted active research so far, mobile devices and their complete ecosystems of downloadable applications are transforming different facets of society leading to the BI&A 3.0 systems in support of highly mobile, location-aware, person-centered, and context-relevant analysis. More recently, the rise of Internet of Things (IoT) together with accelerated access to an enormous scale of data is also fueling the ongoing BI&A trend (Watson, 2019). Intensively Big Data-driven tools and mechanisms have been proposed to improve new and dynamic business decisional-making process, which suggests an emerging BI&A 4.0 phenomenon (Marjanovic & Barbara, 2017; Saggi & Jain, 2018; Hariri et. al., 2019; Watson, 2019). Figure 3 below depicts the most current BI&A evaluation phases and key characteristics adapted and updated from the selective review addressing the RQ.1 *What are the main concepts and evolution of Big Data BI&A aids.*

4.2 On Big Data BI&A Aids Applications and Frameworks

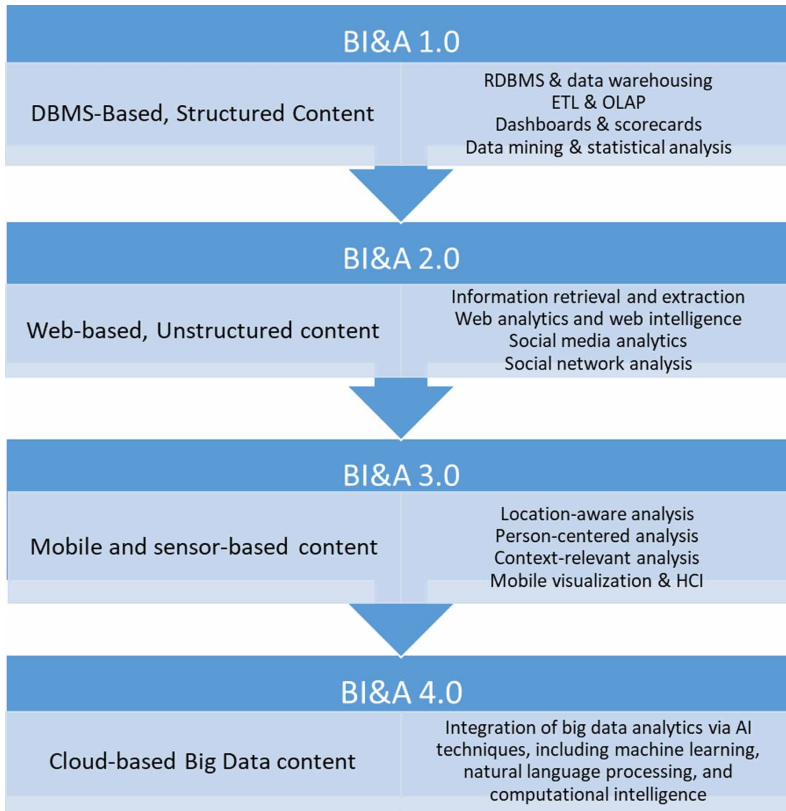
In addition to being data driven, BI&A is highly applied and can leverage challenges and opportunities presented by Big Data and domain-specific analytics needed in many high-impact application areas (Chen et al., 2012; Lim et al., 2013). Big data technologies and analytics allow an organization to leverage the latest big data technologies including predictive analytics, machine learning (ML), IoT (Internet of Things), and the cloud; to glean the most valuable and critical insight from the data being generated by an organization (LaValle et al., 2011; Tien, 2013). Based on the selective review, four particular domains were identified to examine the current and potential value BI&A solutions can derive in the Big Data era, including health care in the United States, public sector administration in the European Union, retail in the United States, and global manufacturing. Together these four domains represented close to 40 percent and roughly 30% of global GDP in 2010 and 2020 respectively and could boost global GDP by \$1.2 trillion to \$2 trillion by 2030 (Manyika et al., 2011; Grijpink et al., 2020). The data and analytics characteristics, potential impacts, and illustrative case studies within each domain are discussed. By carefully analyzing the application and data characteristics, we can present an integrated BI&A application framework that can facilitate the BI&A researchers and practitioners to adopt or develop the appropriate analytical techniques to derive the intended impact in the Big Data era (Chen et al., 2012; Liang & Liu, 2018).

5. HEALTHCARE

Historically the healthcare industry has generated large amounts of data from numerous patient care points of contact, sophisticated medical instruments, and web-based health communities, driven by record keeping, compliance and regulatory requirements, and patient care (Raghupathi & Raghupathi, 2014). Unfortunately, BI&A for Big Data in health care generally lags well behind BI&A applications in other sectors such as Retail and Manufacturing because it has rarely taken advantage of scalable analytical methods or computational platforms (Miller, 2012). By discovering associations and understanding patterns and trends within the Health care Big Data, BI&A can take advantage of the explosion in data to extract new and actionable knowledge for making better informed decisions (Gartner, 2020).

For instance, as Miller (2012) purported, current researchers “*are doing clinical trials using vast troves of observational health care data, analyzing pharmacy and insurance claims data together to identify adverse drug events, delving into molecular-level data to discover biomarkers that help classify patients based on their response to existing treatments, and pushing their results out to physicians in novel and creative ways*”. As such, BI&A has the potential to improve the care quality, enable deeper understanding of patient disease patterns, save patient lives, and lower costs in the healthcare delivery system (Miller, 2012; Raghupathi & Raghupathi, 2014). Data science and predictive analytics can enhance the quality of healthcare provided to each patient. To accomplish so, the current BI&A solutions need to be equipped with advanced techniques targeted at the Big Data challenges, such as machine-learning for pattern recognition, segmentation and predictive modeling, hypothesis-free probabilistic causal approaches (e.g. Bayesian network analysis), symptom–disease–treatment (SDT) association rule mining and clustering, and so on. However, as argued by Manyika et al. (2011), deploying BI&A for Big Data in this sector would need to be accompanied by a range of enablers beyond technology innovation, some of which would require a substantial rethinking of the way health care is provided and funded. For example, in response to current and future pandemics, graph technologies can relate entities across everything from geospatial data on people’s phones to facial-recognition systems that can analyze photos to determine who might have come into contact with individuals who later tested positive for the coronavirus. Machine learning algorithms integrated with graph technologies can be used to search multiple data sources and documents that could help medical and public health experts rapidly discover new possible treatments or factors that contribute to more negative outcomes for some patients (Gartner, 2020).

Figure 3. BI&A Evolution Phases and Key Characteristics (adapted and updated from Chen et al. 2012)



6. PUBLIC SECTOR ADMINISTRATION

Similar to healthcare, the public sector is another large sector facing tremendous pressure to improve its efficiency and productivity. In general, governments have access to vast amounts of digital data but rarely take advantage of the powerful strategies which they could use to improve performance and transparency (Manyika et al., 2011). Proper integration and extension of BI&A strategy and technologies that complement the Big Data management would be necessary, such as massive parallel-processing (MPP) databases, distributed file systems, cloud computing technologies, criminal association rule mining and clustering, criminal network analysis, spatial-temporal analysis and visualization, and multilingual text analytics to mention a few.

Successful applications of BI&A in this sector include homeland and cyber security informatics (Chen et al., 2012), in which security agencies are gathering, processing and analyzing large amounts of security-related data (e.g., criminal records of terrorism incidents and cyber security threats); content analysis and network community analysis of blog contents and bloggers' interaction networks; public transportation (Zaslavsky et al., 2013), in which transportation agencies make use of sensor roadways in order to monitor traffic in real-time to optimum traffic management; tax collections or benefit payments auditing (Brown et al., 2011), in which tax agencies apply automated algorithms that perform systematic, multilevel checks on tax returns and automatically flag returns that require further examination or auditing; and construction and public safety (Zaslavsky et al., 2013), in which public safety agencies utilize embedded sensors with monitoring systems to collect variety of different measurements such as a change in temperature and the concrete reaction to that change for further safety analysis.

7. RETAIL

In contrast to the first two domains, retail is an advanced, progressive sector where the revolution of Big Data first emerged. The retail sector retail has been leveraging BI&A strategies and techniques for decades. A typical example would be the quantification of the impact of user-generated content on consumers' good purchase expenditures, or the development of decision support systems for social media brands and competitive analysis of markets. More recently, businesses have been using vast amounts of data for segmenting customers, identifying emerging trends, improving business decision making, driving more sales, and developing new revenue-making strategies (Fan et al., 2015; Watson, 2019). These data are pulled from the web, such as online searches, posts and messages, as well as from local stores, such as customer movement in the store and fitting rooms. Unlike traditional sales transaction records collected from various legacy systems of the 1980s, the Big Data that businesses today collect from various sources are less structured and often contain rich customer opinion and behavioral information (Chen et al., 2012). Along the process, various analytical techniques have been developed for social media customer opinion analysis and customized recommender systems, such as text analysis and sentiment analysis, association rule mining, database segmentation and clustering, anomaly detection, and graph mining (Adomavicius & Tuzhilin 2005; Pang & Lee 2008).

For example, retail giant Walmart, the largest retailer in the world with more than two million employees and annual sales of around \$450 billion, has been a data-driven company since the 1990s. The company uses innovative BI&A techniques that allowed the retailer to peer into its massive databases of previous transactions to identify customer buying patterns and predict future buying trends (Mayer-Schönberger & Cukier, 2013). Major Internet firms, such as Amazon, Google, and Facebook, also continue to lead the development of web analytics, cloud computing, fog computing which both enhances and complements the cloud by bringing the data processing closer to a cluster of IoT devices, resulting in faster analytics and insights; and social media platforms that offer substantial opportunities for researchers and practitioners to "listen" to the voice of the market from a vast number of business constituents (Chen et al., 2012). Nevertheless, there is still tremendous potential across the industry for businesses to expand and improve their use of BI&A for Big Data, particularly given the increasing ease with which they can collect information on their consumers, suppliers, and inventories (Brown et al., 2011).

8. MANUFACTURING

There are promising solutions enabled by data science that are critical to processing data of high volume, velocity, variety, and low veracity, towards the creation of added-value in smart factories of the future (Gao et al., 2020). Increasingly global and fragmented manufacturing value chains have created new challenges that manufacturers worldwide must overcome to sustain productivity growth (Manyika et al., 2011; Lee et al., 2013). As Manyika et al. (2011) purported, manufacturers will need to leverage a significant amount of digital data to drive efficiency across the extended enterprise and to design and market higher quality products in order to continue achieving increased levels of productivity growth. This sector generates the most datasets, more data than in any other sector, from a multitude of sources including instrumented production machinery for process control, supply chain management systems, monitoring systems that observe the performance of products in action (Manyika et al., 2011). Indeed, the amount of data generated will continue to grow exponentially in this sector. Big data analytics in manufacturing Internet of Things (MIoT), and data analytics in massive manufacturing data can extract huge business values while can also result in research challenges due to the heterogeneous data types, enormous volume and real-time velocity of manufacturing data (Dai et al., 2020).

Using a Boeing jet for example, it generates 10 terabytes (TB) of data per engine every 30 minutes and a single six-hour flight would generate 240 terabyte (TB) of data (Zaslavsky et al.,

2013). In addition, there are about 28537 commercial flights in the sky in United States on any given day. According to Manyika et al. (2011), BI&A for Big data has the potential to enable seven performance improvement areas for manufacturers, affecting the entire value chain: 1) offer further opportunities to accelerate product development and improve product design, through concrete customer input and open innovation; 2) aggregate customer data and make them widely available and enable design-to-value; 3) share data through virtual collaboration sites (idea marketplaces to enable crowd sourcing); 4) implement advanced demand forecasting and supply planning across suppliers; 5) implement lean manufacturing and model production virtually (digital factory) to create process transparency; 6) implement sensor data-driven operations analytics to improve throughput and enable mass customization; and 7) collect after-sales data from sensors and feedback in real time to trigger after-sales services. In short, manufacturers around the globe have tremendous potential to generate value from the use of BI&A with Big Data, integrating data across the extended enterprise and applying advanced analytical techniques to raise their productivity both by increasing efficiency and improving the quality of their products (Brown et al., 2011; Lee et al., 2013).

Figure 4 below summarizes the promising and high-impact BI&A applications to address the challenges and opportunities brought on by the Big Data era in four main domains, namely, healthcare, public sector administration, retail, and manufacturing. This integrated BI&A application framework, addressing both *RQ.2 What are the most relevant Big Data BI&A frameworks aids* and *RQ.3 What are the main domain of applications reported for Big Data BI&A aids*, can facilitate the BI&A researchers and practitioners to adopt or develop the appropriate analytical techniques in each specific domain to derive the intended impact and value in this Big Data era (Chen et al., 2012; Watson, 2019).

8.1 On Big Data BI&A Aids Challenges and Trends

The selective review reveals that a majority of executives in the market believe that their organization's need for Big Data skills and support tools will rise in the future (Sun et al., 2017; Sun & Huo, 2019). With the prominent value proposition, Big Data has also created new challenges for businesses and decision makers across many different industries and jobs. Businesses are collecting vast amounts of data more frequently, yet they are still not grasping the potential of all the data (Delen & Demirkan, 2013). They do not know what to do with all such data. Consequently, decision makers face the challenge to work with huge datasets from multiple and varied sources, make sense of this data, and process the data with adequate tools to gain insights toward an efficient and effective decision-making process (Demirkan & Delen, 2013). Thus, Big Data needs adequate methods and tools for such an aim (Willwhite, 2014; Asllani, 2015; Watson, 2019).

The value promise of Big Data for business executives and managers is to know radically more about their businesses and directly translate that knowledge into efficient and effective decision-making processes in order to better their organizational performance (McAfee & Brynjolfsson, 2012). For this aim, the Business Intelligence and Analytics (BI&A) methods and tools have become their processing strategy of choice. BI&A evolution process can be classified into phases 1.0 (DBMS-based), 2.0 (Web-based), 3.0 (mobile and sensor-based), and 4.0 (cloud-based). According to the selective review, BI&A 4.0 applied to Big Data has enabled some important international organizations to be more competitive in the global environment (Saggi & Jain, 2018; Watson, 2019). To accomplish this goal, the current BI&A 4.0 solutions need to be equipped with advanced techniques targeted at the Big Data challenges, such as machine-learning for pattern recognition; micro-segmentation and predictive modeling; advanced association rule mining and clustering; text and web analytics; sentiment analysis; anomaly detection and graph mining; and signal processing and time series analysis (Delen & Ram, 2018). Figure 5 below depicts the BI&A evolution process with phase 4.0 techniques highlighted to address the Big Data challenges and opportunities, addressing *RQ.4 What are the main trends and challenges for effective decisional support with Big Data BI&A aids*. Figure 6 presents an overview of the Big Data characteristics and corresponding BI&A technology as well

Figure 4. BI&A Application Framework for Big Data in Four Main Domains

Health Care	Public Sector Administration	Retail	Manufacturing
<ul style="list-style-type: none"> • Applications <ul style="list-style-type: none"> • Determine allocation of R&D resources • Clinical trial design • Develop personalized medicine • Analyze disease patterns • Patient claims & records aggregation/synthesizing • Data <ul style="list-style-type: none"> • clinical trials • electronic medical records • claim records, cost estimates • patient behaviors and preferences • Analytics <ul style="list-style-type: none"> • machine-learning for pattern recognition • segmentation and predictive modeling • hypothesis-free probabilistic causal approaches • advanced association rule mining & clustering • Impacts <ul style="list-style-type: none"> • reduced national healthcare expenditure • improved quality of care • improved treatment effectiveness • improved long-term care • enhanced patients' experience 	<ul style="list-style-type: none"> • Applications <ul style="list-style-type: none"> • Create public transparency • Uncover variability in performance of agencies • Using segmentation to tailor services • Reduce fraud and error • Support human decision making with automated algorithms • Data <ul style="list-style-type: none"> • government information • Rules and regulations • citizen feedback and comments • criminal records & terrorism incidents • viruses & cyber attacks • Analytics <ul style="list-style-type: none"> • massive parallel-processing (MPP) DB • distributed file systems • cloud computing technologies • criminal association rule mining/clustering • criminal network analysis • multilingual text analytics • Impacts <ul style="list-style-type: none"> • reduction in cost of errors & fraud • improved public safety & security • improved government transparency • tailored & better services 	<ul style="list-style-type: none"> • Applications <ul style="list-style-type: none"> • Cross-selling • Location based marketing • In-store behavior analysis • Customer micro-segmentation • Sentiment analysis • Placement and design optimization • Pricing optimization • Data <ul style="list-style-type: none"> • point-of-sale transactional data • customer preferences & buying behavior • real-time location data • web search and user logs • customer content • Analytics <ul style="list-style-type: none"> • text & web analytics • sentiment analysis • advanced association rule mining • micro-segmentation & clustering • anomaly detection & graph mining • Impacts <ul style="list-style-type: none"> • increased sales & profit margins • improved inventory management • speedier & more personalized promotions • differentiated & value-added services 	<ul style="list-style-type: none"> • Applications <ul style="list-style-type: none"> • Accelerate & improve product R&D • Aggregate customer data & enable design-to-value • Implement advanced demand forecasting & supply planning • Trigger after-sales services • Data <ul style="list-style-type: none"> • product lifecycle data • real-time defects from production plants • instrumented production machinery data • end-to-end supply chain • product usage & performance data • Analytics <ul style="list-style-type: none"> • sensor data-driven operations analytics • ensemble learning • signal processing & time series analysis • Spatial analysis & simulations • Predictive modeling & demand forecasting • Impacts <ul style="list-style-type: none"> • accelerated & improved product R&D • open innovation • increased efficiency in production • improved demand forecast & supply plan

as methodological solutions to mitigate the challenges, while integrating investigation results on RQ.1 through RQ.4.

From an application perspective, executives and leaders of global organizations are facing these new challenges of effective decision making in the Big Data era and they desire practical BI&A solutions that can help them convert the Big Data into strategic insights and impacts. This integrative review presented in this paper adds to this body of knowledge and helps facilitate additional research and practical endeavors. A logical evolution of the origins and techniques of BI&A for Big Data were identified and presented. Based on the richness and variety of BI&A application and research findings, we present the following recommendations and cautions to executives and leaders interested in such productive yet challenging investments:

- All industry sectors face the challenges of effective and efficient decision making in the Big Data era and the current **BI&A 4.0 solutions can help them become more competitive data-driven companies.**
- To effectively address the Big Data challenges, the current **BI&A 4.0 solutions need to be equipped with advanced techniques** depending on the involved data types, sources, structures, and other organizational characteristics.

- Practitioners across different industries can utilize **the presented integrated BI&A application framework** to adopt or develop appropriate BI&A techniques and solutions to derive the intended impact in the Big Data era.
- BI&A for Big Data brings forward **a new culture and way of decision making**. Besides technical challenges, managerial challenges of using BI&A in the Big Data era must be addressed to reap the full benefits of that transition.

This selective review research reveals that the BI&A evolution process has experienced drastic changes in its execution by organizations, its theoretical conceptualization by researchers, and its practical implications in the Big Data era. The main shift on the BI&A evolution process can be stated as an evolution from traditional analytical and statistical techniques with structured data sets in highly predictable and cooperative business environment, to data-driven discovery and highly proactive and creative decision-making utilizing advanced analytical techniques with unstructured and massive data sources to cope with a highly dynamic global business environment in the Big Data era.

9. CONCLUSION

With an aggressive push towards Web 2.0 and Internet of Things (IoT) or the Industrial Internet, data has become more accessible and ubiquitous in the global environment. In view of the increasing importance of Big Data, an ever-increasing number of companies are attempting to leverage on these data to exploit new opportunities and gain an in-depth understanding of hidden values (Raguseo, 2018). This Big Data phenomenon and trend necessitate the appropriate techniques and solutions to convert massive data into useful information and actionable knowledge. It is a simple formula: Using BI&A for Big Data leads to better predictions, and better predictions yield better decisions (McAfee & Brynjolfsson, 2012; Watson, 2019).

In this paper, we have conducted a selective review on the BI&A evolution phases and key characteristics, the Big Data challenges and opportunities for BI&A, and illustrative BI&A applications to address the Big Data challenges and opportunities. Along the process, we have developed an integrated and organized view on the BI&A evolution process and presented an integrated BI&A application framework to help organizations adopt or develop the appropriate BI&A solutions to derive the desired impact in the Big Data era. This paper also elicits a set of practical recommendations to executives and leaders in organizations worldwide for interpreting the BI&A literature and applying the rich body of knowledge for IT practitioners. Given the importance and complexity of BI&A and Big Data phenomenon, we encourage and anticipate continued research efforts to investigate and establish advanced and updated conceptualizations and frameworks to cope with this complex yet critical subject.

Figure 5. BI&A Evolution & Phase 4.0 techniques to address Big Data Challenges

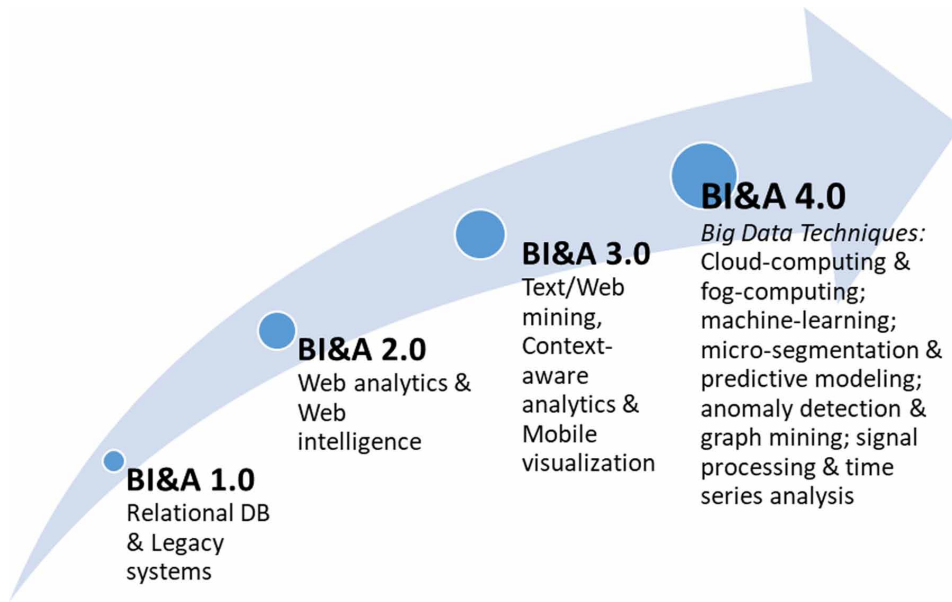


Table 2. Big Data challenges and corresponding BI&A solutions (adapted from Asllani, 2015)

Big Data dimension	Challenges to BI&A	Technology-based Solutions	Methodology-based Solutions
Volume	Managing large and rapidly increasing data sources	<ul style="list-style-type: none"> Advanced software programs able to process large number of constraints and decision variables 	<ul style="list-style-type: none"> Standardize the ETL processes to automatically capture and process input parameters Encourage system-driven versus user-driven optimization programs
Variety	Dealing with heterogeneity of data sources Dealing with incomplete data sets	<ul style="list-style-type: none"> Relational database systems and declarative query language to retrieve data input for optimization models ETL toward specialized optimization driven Data Marts 	<ul style="list-style-type: none"> Add data structuring prior to analysis Implement data cleaning and imputation techniques
Velocity	Managing large and rapidly changing data sets Reaching on-time optimal solutions for operational business intelligence	<ul style="list-style-type: none"> Advanced optimization software with the capability to reach optimal solutions within a feasible amount of time Use optimization packages that directly connect to operational data bases 	<ul style="list-style-type: none"> Consider a trade-off between less than optimal but time feasible and practical solution and optimal but complex and often delayed solutions
Value	Discovering hidden value from large volume data sets Filtering noises and searching for hidden patterns and knowledge through powerful processing	<ul style="list-style-type: none"> Advanced cloud computing to address the challenge of processing demand Scalable implementation of computerized machine-learning for pattern recognition 	<ul style="list-style-type: none"> Clean and filter noises prior to performing analytics Adopt scalable solution for data acquisition and analysis through two-phase process, crawling and processing

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