Chapter 3
From Business Intelligence to Big Data:
The Power of Analytics

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ABSTRACT

Boundaries between business intelligence (BI), big data (BD), and big data analytics (BDA) are often unclear and ambiguous for companies. BD is a new research challenge; it is becoming a subject of growing importance. Notably, BD was one of the big buzzwords during the last decade. BDA can help executive managers to plan an organization's short-term and long-term goals. Furthermore, BI is considered as a kind of decision support system (DSS) that can help organizations achieving their goals, creating corporate value and improving organizational performance. This chapter provides a comprehensive view about the interrelationships between BI, BD, and BDA. Moreover, the chapter highlights the power of analytics that make them considered as one of the highly impact's organizational capability. Additionally, the chapter can help executive managers to decide the way to integrate BD initiatives as a tool, or as an industry, or as a corporate strategy transformation.

INTRODUCTION

We are in the middle of data explosion. According to Statistica (2020), the size of the digital universe in 2013 was estimated at about 50 zetabytes, it is expected to reach 175 zetabytes by 2025. The global market for software, hardware, and services for storing and analyzing big data is estimated to triple in size in the next five years (Statistica, 2020).

According to Forbes report, "The Global State of Enterprise Analytics, 2020", Cloud Computing, IoT, and Artificial Intelligence/Machine Learning will have the greatest impact on enterprises' analytics initiatives over the next five years. Across all enterprise executives globally, Big Data, 5G, and Security/Privacy concerns are predicted to have the greatest impact (Columbus, 2019). Furthermore, advanced and predictive analytics are dominating enterprises' analytics initiatives today, improved efficiency and

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productivity; achieving faster for more effective decision-making; and driving better financial performance are the top three benefits enterprises which are gaining from analytics (Columbus, 2019).

Going back to the 1990s, after the information warehousing quickly vanished, the BI era took over. This era introduced a way which is not only to reorganize data, but also to transform it into much cleaner and easier to follow. In this era, BI was pushed notably by the introduction of Data Warehousing (DW) and On-Line analytical Processing (OLAP) that provide a new category of data-driven DSS. OLAP tools provide users with the way to browse and summarize data in an efficient and dynamic way (Alnoukari, Alhawasli, Alnafea, & Zamreek, 2012). According to Ram, et al. (2016), BI is focusing mainly on structured and internal data. Therefore, many of valuable information embedded in the unstructured and external data remain hidden, which leads to an incomplete view and limited insights, thus biased decision-making.

Currently, the new technologies generate huge amount of data arriving from many sources including; computers, smartphones, tablets, sensors, social media, audios, videos, IoT, clickstreams, databases transactions, and so on (Walls & Barnard, 2020; Braganza, Brooks, Nepelski, Ali, & Moro, 2017; Fosso Wamba, Gunasekaran, Akter, Ren, Ji-fan, Dubey, & Childe, 2017). Wal-Mart generates about 2.5 petabytes per hour. Fiber optic cable, the most efficient media for data transfer, can transfer up to 100 gigabits per second. Wal-Mart, simply mean, produces more data than it could transfer to any another place (Brock & Khan, 2017).

Traditional tools are unable to store, manage and analyze such hug data. This situation leads to the creation of the new big data global phenomenon. In 1997, Michael Cox and David Ellsworth first used the word “Big Data” to explain data visualization and the challenges which would pose to computer systems (Wang, Kung and Byrd, 2018). BD moves away from traditional data management onto new methods focusing on data discovery, data integration and data exploitation within the context of “big” data. The word “big” does not only imply size, but rather the ability to produce insights, and manage complex types (Wang, Kung and Byrd, 2018). This leads to the adoption of famous BD three V’s (Volume, Velocity, and Variety). The evolution of BD took place during the period from 2001 to 2008 when new tools and technologies were able to manage immense amount of data. 2009 was the year of the BD revolution where it was able to handle and manage unstructured data, in addition to the move from static environments into cloud-based environments (Wang, Kung and Byrd, 2018).

Another important challenge, BD technologies have to process BD in real-time (streaming processing). For example, the large hadrons collider (LHC) generates more raw data than the CERN computing grid can store; thus data has to be instantly analyzed, hence necessities the parallel and distributed computing (Brock & Khan, 2017).

Thus, in the light of this, the main goal of this study is to analyze recent literature of BD, and to find the relationship between BI, BD and BDA. Moreover, the study highlights the power of analytics that make them considered as one of the highly impact’s organizational capability.

To achieve this goal, a conceptual literature review was adopted to find all the studies that relate BI with BD. Then, an analysis phase was required to find the interrelationship between both domains. Finally, the study helps managers to decide the way to adopt BD initiatives.

The remainder of this paper is organized as follows. The next section looks at the fundamentals of BI, BD, and BDA. Then a section discussing in details the relationships between BI, BD, and BDA. Thereafter, a section discusses big data analytics capability, and highlights the power of analysis in the current era. Then, the paper provides an overview about the current trends in BD initiatives adoption, with real examples and case studies. The final section ends this paper with some concluding remarks and future work.

BACKGROUND

Business Intelligence Overview

BI has received a widespread attention from scholars and professionals over the past three decades. BI has become an important technology to improve organizational performance (Alnoukari, Alhawasli, Alnafea, & Zamreek, 2012).

BI can be defined as a set of theories, methodologies, architectures, systems and technologies that support business decision making with valuable data, information and knowledge (Alnoukari, 2009; Sun, Zou, & Strang, 2015). Alnoukari et al. (2012) define BI as "The use of all organization's resources: data, applications, people and processes in order to increase its knowledge, implement and achieve its strategy, and adapt to the environment's dynamism". Jin & Kim (2018) consider BI as an information value chain gathering raw data that turned into useful information for better decision-making that in turn creates value and improves organizational performance.

BI main components include; tools for multidimensional data analysis (OLAP) and data mining, tools for data warehousing and DB management, tools for ETL, and tools for visualizations (Alnoukari, Alhawasli, Alnafea, & Zamreek, 2012; Sun, Zou, & Strang, 2015).

Arguably, BI can be seen as a DSS that includes the overall process of gathering huge data, extracting useful information, and providing analytical capabilities (Jin, & Kim, 2018). Other studies have been seen BI as an Information System to support decision-making (Sun, Zou, & Strang, 2015; Alnoukari, 2009), it consists of the following main steps; analysis, insight, action, and performance measurement (Sun, Zou, & Strang, 2015). Jin & Kim (2018) argue that the concept of BI has been growing according to the applications and technologies that support firm's to gather, store, analyze, and access data more effectively.

Self-service oriented BI architecture in an emergent BI approach that can empower casual users to perform custom analytics and to drive actionable information without having to involve BI specialist (Passlick, Lebek, & Breitner, 2017). Data lake implementation can be considered as a source for self-service BI (Llave, 2018).

Big Data Definition: From 3 V's To 7 V's

Literature refers to the three V's when trying to define BD. Many academics use this definition in the literature to date (e.g. Braganza, Brooks, Nepelski, Ali, & Moro, 2017). The three V's are volume, variety, and velocity. The main source of this exponentially increased data coming from the unstructured data of social networks, blogs, text messages, videos and audios (Braganza, Brooks, Nepelski, Ali, & Moro, 2017). Variety refers to the different types of data that can be manipulated using BD technologies (Faroukhi, El Alaoui, Gahi, & Amine, 2020). Structured, semi-structured, and unstructured data types are currently under BD process (Faroukhi, El Alaoui, Gahi, & Amine, 2020). Unstructured data is the challenge key that allows BD to overcome the main deficiencies of the traditional methods. Velocity refers to the speed at which data is generated and delivered (Faroukhi, El Alaoui, Gahi, & Amine, 2020).

Insights are close to the real time decision-making (Walls & Barnard, 2020). According to the three V's dimensions, BD was defined as; large volumes of extensively varied data that are generated, captured, and processed at high velocity (Walls & Barnard, 2020).

An additional two V's were embedded later to the set of BD definition. These are Value and Veracity. Value refers to the insights and benefits that can be gained from BD (Chen, Mao, & Liu, 2014; Erevelles, Fukawa, & Swayne, 2016; Faroukhi, El Alaoui, Gahi, & Amine, 2020). Veracity concerns to the anomalies and uncertainties in data, due to inconsistencies and incompleteness (Faroukhi, El Alaoui, Gahi, & Amine, 2020). The process of precluding bad data is therefore important to extract reliable insights (Faroukhi, El Alaoui, Gahi, & Amine, 2020). Based on the five V's definitions, Fosso Wamba et al. (2015) define BD as "a holistic approach to manage, process and analyze 5 V's (i.e., volume, variety, velocity, veracity and value) in order to create actionable insights for sustained value delivery, measuring performance and establishing competitive advantages.".

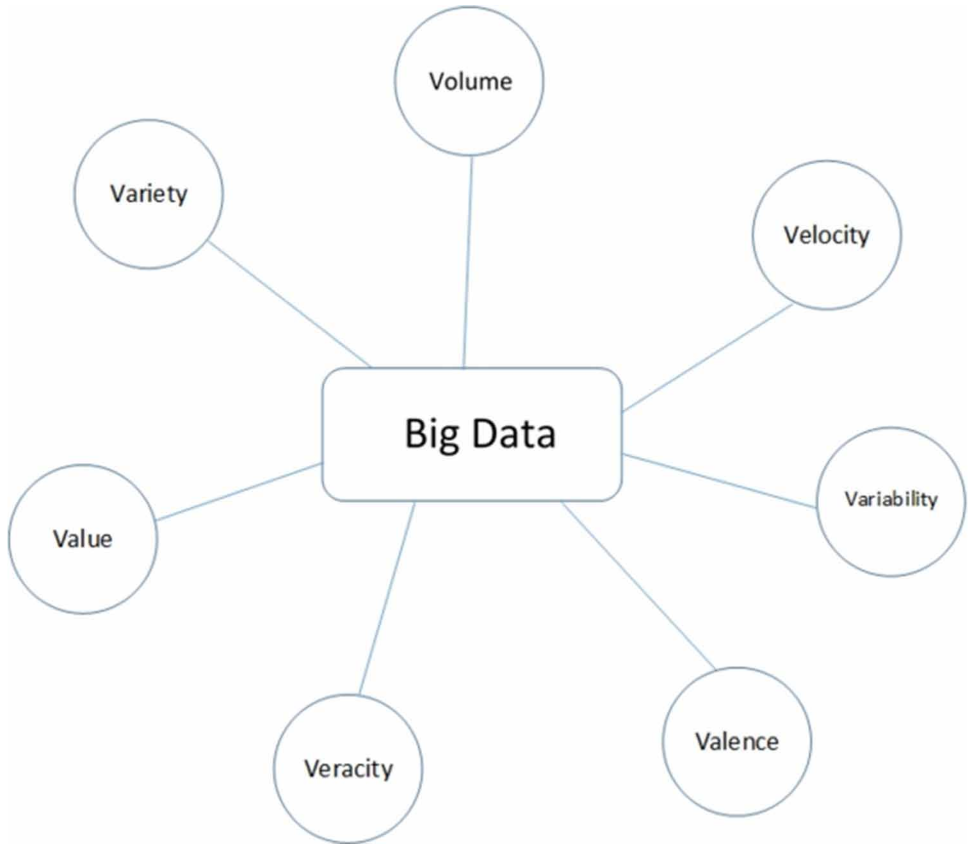
The five V's are lately extended to include Valence and Variability and became seven V's definition in order to provide the whole encompassing view of BD (Erevelles, Fukawa, & Swayne, 2016; Braganza, Brooks, Nepelski, Ali, & Moro, 2017). Valence refers to the connectedness of data collected, and Variability refers to constant and rapid changing of the data meaning (Braganza, Brooks, Nepelski, Ali, & Moro, 2017). With these all seven V's, BD is becoming a source of innovation and competitive advantage (Erevelles, Fukawa, & Swayne, 2016). Based on the seven V's definitions, we can update Fosso Wamba et al. (2015) BD definition as "a holistic approach to manage, process and analyze the 7 V's (i.e., volume, variety, velocity, veracity, value, valence, and variability) in order to create actionable insights for sustained value delivery, measuring performance, establishing competitive advantages, and becoming a source of innovation" (Figure 1).

Big Data Analytics Fundamentals

BDA is considered as a disruptive technology that will reshape BI (Fan, Lau, & Zhao, 2015). Sun et al. (2015) considered BDA as an emerging science and technology involving the multidisciplinary state-of-art information and communication technology, statistics, operations research, machine learning, and decision sciences for BD (Sun, Zou, & Strang, 2015). Hence, it encompasses a wide range of mathematical, statistical and modeling techniques. From strategic perspectives, BDA differs from traditional data analytics in the way that it offers the possibilities to discover new opportunities, to offer the customer a high-value and innovative products and services (Davenport, 2014).

According to Sun et al. (2015), BDA can be defined as the process of collecting, organizing and analyzing BD to discover patterns, knowledge, and intelligence as well as other information within the BD. Fan et al. (2015) define BDA as the domain that uses data analytics to gain business insights that will lead firms to improve decision-making. Jin & Kim (2018) define BDA as the overall process of applying advanced analytics to identify patterns, trends, correlations, and other useful techniques. Al-Qirim et al. (2019) argue that BDA is the process of uncovering actionable knowledge patterns from BD. Polese et al. (2019) argue that BDA can enhance the comprehension of business opportunity, and gain better insight into customer behavior, and services/products effectiveness. Insights provided by BDA can improve the efficiency of the organizations' whole operations, as well as the strategy (Walls & Barnard, 2020; Holmlund, Van Vaerenbergh, Ciuchita, Ravald, Sarantopoulos, Villarroel-Ordenes, & Zaki, 2020). Moreover, Sadovskyi et al. (2014) argue that BDA adds additional characteristics to the conventional data analysis including; innovated technologies and skills that enable organizations to own

Figure 1. Dimensions of Big Data



deep analytical capabilities, and integration of wide range of data types from a large number of relatively unreliable data source in order to provide a meaningful and reliable source of business information. Aligned with this viewpoint, Fosso Wamba et al. (2017) and Holmlund et al. (2020) consider BDA as an innovative approach to deliver sustained value, and enable competitive advantage (Mikalef, Pappas, Giannakos, Krogstie, Lekakos, 2016). BDA allows firms to manage and analyze strategy through data lens (Fosso Wamba, Gunasekaran, Akter, Ren, Ji-fan, Dubey, & Childe, 2017; Shams, & Solima, 2019).

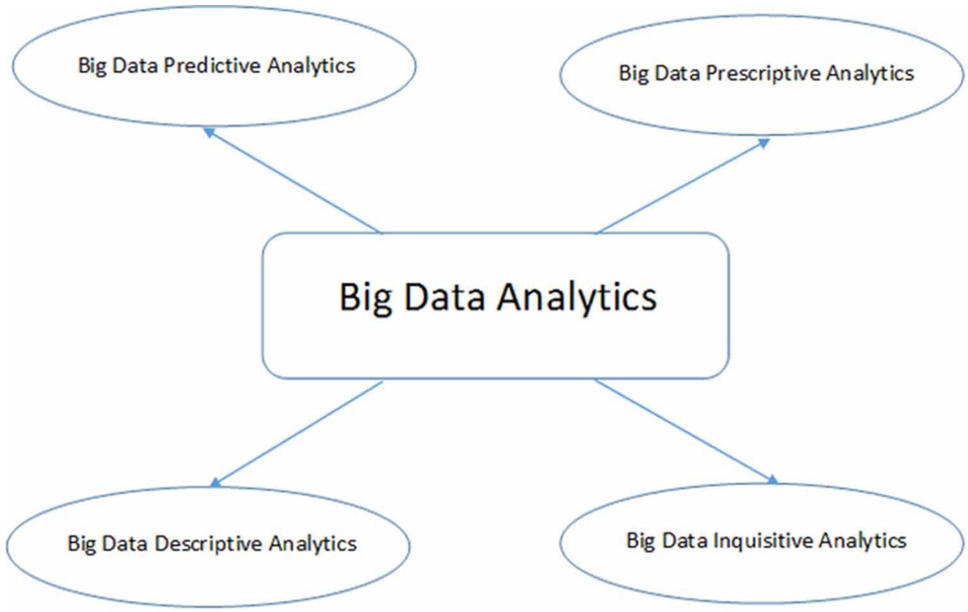
BDA has four different levels of analysis (Figure 2): descriptive, inquisitive (or diagnostic), predictive, and prescriptive (Holmlund, Van Vaerenbergh, Ciuchita, Ravald, Sarantopoulos, Villarroel-Ordenes, & Zaki, 2020; Sun, Zou, & Strang, 2015). After generating BDA, organizations are able to generate different insights including market, behavioral and attitudinal insights. Descriptive BDA is related to "What happened?" question answers. This kind of analytics helps describing the situation further analysis (Holmlund, Van Vaerenbergh, Ciuchita, Ravald, Sarantopoulos, Villarroel-Ordenes, & Zaki, 2020). Typical examples include descriptive statistics using charts, cross tabulation, or clustering graphs. Inquisitive DBA is related to "Why did things happen?" question answers (Holmlund, Van Vaerenbergh, Ciuchita, Ravald, Sarantopoulos, Villarroel-Ordenes, & Zaki, 2020). This kind of analytics helps validating research hypotheses, determining causation, and identifying variables to achieve desired results. Typical examples include statistical inference techniques or factor analysis (Holmlund, Van Vaerenbergh, Ciuchita, Ravald, Sarantopoulos, Villarroel-Ordenes, & Zaki, 2020). Predictive BDA is related to "What could happen?" question answers. This kind of analytics helps predicting future trends. Typical examples include forecasting models, classification models, or neural networks (Holmlund, Van Vaerenbergh, Ciuchita, Ravald, Sarantopoulos, Villarroel-Ordenes, & Zaki, 2020. Prescriptive BDA is related to "What should happen?" question answers. This kind of analytics helps providing quantifiable answers when solving a problem (Holmlund, Van Vaerenbergh, Ciuchita, Ravald, Sarantopoulos, Villarroel-Ordenes, & Zaki, 2020). Typical examples include optimizations modeling, queuing modeling, or simulations. Building upon this tautology; BDA has been used successfully in many areas (Holmlund, Van Vaerenbergh, Ciuchita, Ravald, Sarantopoulos, Villarroel-Ordenes, & Zaki, 2020; Palem, 2014). Saidali et al. (2019) propose combining BDA and classical marketing analytics in order to gain valuable and real time insights, thus improve the marketing decision-making process. Different analytics have achieved great success including; usage based insurance, predictive maintenance, Epidemic outbreak detection, and sentiment analysis (Palem, 2014). Ram, et al. (2016) listed five main advantages when applying BDA; increasing data visibility, improving organizational performance, improving meeting customer's needs, revealing valuable insights, and revealing new business models, products and services. In their recent research, Faroukhi et al. (2020) propose a set of BDA tools that provide the ability to deal with various data status. DBA tools are categorized into three families; storage, processing, and visualization.

There is a strong relationship between BDA and strategic management (Şen, Körük, Serper, & Çalış Uslu, 2019; Mikalef, Pappas, Giannakos, Krogstie, Lekakos, 2016). BDA in the lens of strategic management are the capabilities required to gain organizational performance (Walls & Barnard, 2020). BDA provide the ability to show behavioral insights about customers (Suoniemi, Meyer-Waarden, & Munzel, 2017); these insights could be turned into strategic advantages (Şen, Körük, Serper, & Çalış Uslu, 2019). BDA can also improve the metrics used in decisional processes (Fosso Wamba, Gunasekaran, Akter, Ren, Ji-fan, Dubey, & Childe, 2017). Target Corporation is an example of how BDA can be used to track customers purchasing behaviors and predict future trends (Şen, Körük, Serper, & Çalış Uslu, 2019). A personalized purchasing recommendation program is another example (Şen, Körük, Serper, & Çalış Uslu, 2019). Furthermore, Şen et al. (2019) argue that BDA can be used in simulation modeling to gain insight knowledge about the simulated system, and determine the model parameters used in the simulation process.

The Relationship between Business Intelligence, Big Data and Big Data analytics

Scholars argue that there is a close relationship between BI, BD & BDA because BI provides the methodological and technological capabilities for data analysis (e.g. Llave, 2018; Sun, Zou, & Strang, 2015). BI supports firm's decision making with valuable data, information, and knowledge (Alnoukari & Hanano, 2017), hence BDA can be seen as a part of BI (Sun, Zou, & Strang, 2015). In addition, both BI and BDA share some common tools supporting decision-making process. Furthermore, BI and BDA are common in emphasizing valuable data, information, and knowledge. Moreover, BI and BDA involve interactive visualization for data exploration and discovery. Even more, BI is currently based on four cutting-age technology pillars of cloud, mobile, big data, and social technologies; they are also supported effectively by BDA as a service and technology (Passlick, Lebek, & Breitner, 2017; Sun, Zou, & Strang, 2015). Sun et al. (2015) further argue that BDA is an essential tool for developing BI from at least technological and data viewpoints. From technological viewpoint, BDA is data-driven and business oriented techniques, hence; facilitates firm's decision-making and then improves BI. From data viewpoint, knowledge dis-

Figure 2. Big Data Analytics Levels



covery is the core of BDA & BI systems (Sun, Zou, & Strang, 2015). Jin & Kim (2018) consider that BI's "raw data" have been expanded into "Big Data" due to the advanced technology capability. Hence, it is logical to consider that BI/BD/BDA are not independent concepts. Consequently, it is beneficial to integrate all of them into an integrated DSS incorporating all processes from data gathering to data analytics and insights to decision making (Jin, & Kim, 2018). Fan et al. (2015) argue that BDA supports marketing intelligence by providing the ability to monitor customer opinions toward a product, service, or company using social media mining techniques. Fan et al. (2015) further argue that customer opinion mining is a key factor for strategic marketing decision that can be based on multiple data sources including; social media, transactions, surveys, and sensors, can be applied to discover marketing intelligence (Fan, Lau, & Zhao, 2015). Analytical models based on single data source may provide limited insights that consequently lead to biased business decisions. Using multiple and heterogeneous data sources can provide a holistic view of the business and result in better decision-making (Fan, Lau, & Zhao, 2015). Fan et Al. (2015) conclude that big data and its applications on BI have great potential in generating business impacts. In the same vein, Kimble & Milolidakis (2015) argue that BI generated from BD could be in immense value. Sun et al. (2015) argue that due to the dramatic development of BD technologies, BI is currently facing new challenges and opportunities; that is how to use BDA to enhance BI becoming a big issue for organizational performance (Sun, Zou, & Strang, 2015).

However, other scholars highlight many of BI drawbacks when comparing with BD/BDA (e.g. Llave, 2018; Ram, Zhang, & Koronios, 2016; Marín-Ortega, Dmitriyevb, Abilovb, & Gómezb, 2014). During the 2000s, BI was becoming a strategic direction that was adopted by business and technology leaders. BI was based on technology-driven data analytics that extracts usable information (Faroukhi, El Alaoui, Gahi, & Amine, 2020; Marín-Ortega, Dmitriyevb, Abilovb, & Gómezb, 2014). These tools provide the decision-makers with the ability to use the analytical results delivered by the reports, dashboards, and data visualizations. However, BI focuses primarily on structured and internal enterprise data, overlooking valuable information embedded in unstructured and external data (Marín-Ortega, Dmitriyevb, Abilovb, & Gómezb, 2014). This could result in an incomplete view of the reality, and biased enterprise's decision-making (Llave, 2018; Ram, Zhang, & Koronios, 2016; Marín-Ortega, Dmitriyevb, Abilovb, & Gómezb, 2014). Scholars highlight some of BI implementation drawbacks (e.g. Marín-Ortega, Dmitriyevb, Abilovb, & Gómezb, 2014) such as the inability to focus on individual needs, lack of business context information that forces users to understand the semantics of data by themselves, poor alignment between business and IT, and high costs related to model time for new BI implementation. BI classical data analytics are unable to acquire valuable business insights (Saidali, Rahich, Tabaa, & Medouri, 2019). BD insights close the knowledge and time gaps of the traditional methods (Walls & Barnard, 2020). According to Marín-Ortega et al. (2014), data management is the most critical and stressing stage during BI development due to its time consuming. Most of the BI solution providers are focusing on the technological part of data management stage rather than the availability of all the required information (structured and unstructured) to build a good solution. In their recent research, Faroukhi et al. (2020) listed some of the differences between BI and BD/BDA such as; BI is based on File-Based or Object-Based storage models; whereas BD is based on Block-Based storage model. Additionally, BI is based on traditional database data model such as SQL databases and data warehouses. However, traditional databases cannot meet BD challenges, mainly storing and processing hug amount of unstructured data; hence, distributed storage and NoSQL databases are mainly adopted for BD data model (Faroukhi, El Alaoui, Gahi, & Amine, 2020). In the same vein, the hardware storage infrastructure for BI is mainly based on storage devices; whereas, BD requires additional storage infrastructure such as storage network infrastructure and storage virtualization. Furthermore, BD requires distributed processing infrastructure in order to be able to share data, calculations, and processing on over several interconnected nodes. However, traditional BI does not require such distributed processing infrastructure (Faroukhi, El Alaoui, Gahi, & Amine, 2020). Finally, and from analytical viewpoint, descriptive and predictive analyses were mainly developed by BI traditional systems; whereas, BD provides the ability to effectively develop and use additional analytics capabilities such as prescriptive and diagnostic analysis (Faroukhi, El Alaoui, Gahi, & Amine, 2020).

One of the suggested approaches is to fix the ETL (Extract, Transform, and Load) stage bottleneck (Marín-Ortega, Dmitriyevb, Abilovb, & Gómezb, 2014). In typical BI infrastructure, ETL stage starts extracting raw data from Operational Data Sources (ODS), then transforming the raw data into a normalized form, before loading the processed data into the data warehouse. Processing raw data during the transformation phase is critical. A DW typically consolidates a multitude different ODS with multiple schemas; therefore, the raw data must be normalized. In addition, the ODS may contain corrupted, erroneous, or missing data; therefore, the process of cleansing and consolidating data is required (Alnoukari, Alhawasli, Alnafea, & Zamreek, 2012). According to Marín-Ortega et al. (2014), ETL technologies have not been improved in scalability and performance at the same level with the DW technologies. Consequently, most of the BI infrastructures are facing serious bottleneck; data cannot be easily transformed and loaded into the DW in an acceptable time, whereas, the decision makers are looking for real time information. One of the suggested approaches to tackle the ETL serious bottleneck is to throw the transformation phase to the end of the ETL after the loading phase. Hence, ETL is becoming ELT. The main advantage of this switch is that ELT allows firstly extracting and loading data, then applying on-demand transformations according to business needs. In addition, ELT allows to apply and to re-apply data transformation in accordance to the changes in the environment. This provides ELT the flexibility needed to respond to the market changes. As a result, ELT addresses the issue related to design BI solutions in shorter time, as well as, provides the BI with the flexibility to reflect environmental changes. Passlick et al. (2017) proposed BI/BDA architecture model that support both traditional BI analytical reports, and BDA. The proposed architecture model integrates BI components with the BD ones. The data processing layer uses the classic ETL process, extended by the possibility to perform the BD EL(T) process. In addition, in the storage and analysis infrastructure layer, data integration can be done using the classic DW, as well as other BD technologies such as in-memory databases, or Hadoop clusters (Passlick, Lebek, & Breitner, 2017).

Another suggested approach is to integrate the Data Lakes with BI (Llave, 2018). Llave (2018) argues that Data Lakes has made it possible for BI to acquire data without caring of its structure. It is a huge capability to store inexhaustible amounts of raw data without performing any data transformation. Data transformation is considered as a bottleneck when using ETL process between the data sources and DW. Hence, it is similar to ELT, where the transformation is performed in the last step (Llave, 2018).

Data monetization is one of the concepts that has seen notable evolution starting BI era, until the BD era (Faroukhi, El Alaoui, Gahi, & Amine, 2020). Data monetization is a new concept that relies on using the data from organization to generate profit. Explicit data monetization is selling the data directly for cache, or sharing the data, whereas, implicit data monetization is an indirect way relying on that data to create value by enhancing own data-based products (Faroukhi, El Alaoui, Gahi, & Amine, 2020). During the BI era, data monetization was generally implicit, delivered by descriptive analytics. Production data was generally used for internal purpose. Thereafter, data monetization gain popularity and critical evolution during the BD era. Data monetization is becoming attractive in the era of BD (Faroukhi, El Alaoui, Gahi, & Amine, 2020). Data is integrated from external and internal sources that results in advanced analytical capabilities based on data-driven products and services. This allows for explicit monetization by selling data and provides the agility required for creating and monetizing knowledge. Faroukhi et al. (2020) argue that monetizing BD can be articulated based on the following business models directions; extracting customers-based activities data (data extractors), collecting and selling data (data providers), aggregating services (data aggregators), and providing technical platforms that enable processing, consuming and sharing data (technical platform providers). Monetizing BD provides firms with the ability to unlock value, and maximize the data-driven capability (Faroukhi, El Alaoui, Gahi, & Amine, 2020).

Big Data Analytics Capability: The Analytics Power

The complexity nature of BD stems from the difficulties in dealing with huge data sources, dealing with the complexity nature of the data itself, and the data processing to generate data insights (Al-Qirim, Rouibah, Serhani, Tarhini, Khalil, Maqableh, & Gergely, 2019). Data and information cannot, themselves, provide insights. Data insights could be generated by data transformation through analysis and interpretation, values are gained through the ability to drive actions (Holmlund, Van Vaerenbergh, Ciuchita, Ravald, Sarantopoulos, Villarroel-Ordenes, & Zaki, 2020). BD is one of the organization's resources that are necessary but not sufficient to create a Big Data Analytics Capability (BDAC), since many other firms are able to collect huge data from different resources (Gupta, & George, 2016). BD initiatives and BDAC can lead to improved organizational performance through value creation, better strategic decision-making, gains in competitive advantage, efficiency gains, improved marketing and increased innovation (Walls & Barnard, 2020). The term BDAC has been referred to in literature as the "next big thing in innovation", "fourth paradigm of science", "next frontier for innovation, competition, and productivity", "new paradigm of knowledge assets" and "next management revolution" because of the universal adoption of BDA technologies (Fosso Wamba, Gunasekaran, Akter, Ren, Ji-fan, Dubey, & Childe, 2017). In their recent research, Walls & Barnard (2020) adopt BDAC definition as "the holistic approach to managing, processing and analyzing huge volumes of incongruent data to determine actionable ideas and reactions to the data for sustained value and competitive advantage". BDAC refers to the organizational capabilities that can enable firms to analyze their huge data with nontraditional methods using BD tools and techniques; hence, producing insights that enable data-driven decision-making process (Dubey, Gunasekaran, & Childe, 2018). In the same vein, Akter et al. (2016) define BDAC as the competence to provide business insights using data management, technology, and talent capability to transform business into a competitive advantage and gain business value. Therefore, BDAC can be seen as an integration of the following three intertwined capabilities; big data analytics management capability, big data analytics infrastructure capability, and big data analytics talent capability (Walls & Barnard, 2020; Fosso Wamba, Gunasekaran, Akter, Ren, Ji-fan, Dubey, & Childe, 2017). Gupta, & George (2016) refer them as; tangible, human and intangible resources. Big data analytical management capability ensures the proper decision-making. It can be enhanced by improving the quality of planning, investment, coordination, and control (Walls & Barnard, 2020; Fosso Wamba, Gunasekaran, Akter, Ren, Ji-fan, Dubey, & Childe, 2017; Akter, Fosso Wamba, Gunasekaran, Dubey, & Childe, 2016). Big data analytical technology capability refers to the BDA platform flexibility that effectively enables the developing, deploying and supporting firm's resources. It can be improved by enhancing the performance of the BDA platforms in terms of connectivity, compatibility, and modularity (Walls & Barnard, 2020; Fosso Wamba, Gunasekaran, Akter, Ren, Ji-fan, Dubey, & Childe, 2017; Akter, Fosso Wamba, Gunasekaran, Dubey, & Childe, 2016). Big data analytical talent capability refers to the ability of an analytics professional to perform assigned tasks in the BD environment. Akter et al. (2016) argue that analysts should be competent in four important skills, technical knowledge (e.g., database management); technology management knowledge (e.g., visualization tools, and techniques management and deployment); business knowledge (e.g., understanding of short-term and long-term goals); and relational knowledge (e.g., cross-functional collaboration using information). Nocker & Sena (2019) argue that most organizations treat talent analytics as a capability, not as a resource, in order to contribute to value creation. This is in line with the Dynamic Capability Theory where talent analytics capabilities may include; learning capability, as organizational learning should support the implementation of talent analytics across the organization, coordinating capability between different organization sections so that talent analytics can create value, and technical capability for processing HR data.

Wang et al. (2018) listed some of the BDAC in the health care such as; analytical capability for patterns of care, unstructured data analytical capability, decision support capability, predictive capability, and traceability. Holmlund et al. (2020) classified customer experience insights as attitudinal/ psychographic, behavioral, and market insights. Attitudinal/ psychographic insights provide knowledge about satisfaction, advocacy, and valuable efforts by organizations. Behavioral insights help organizations with the knowledge about the behavioral aspect and consequences of customer experience. Market insights are extremely valuable as they are related to the knowledge about organizational performance in terms of the customer experience in relation with the marketplace.

Cloud computing and BD are complementary approaches (Lněnička, & Komárková, 2015). The marriage between cloud computing and BD derived Big data Analytics as a Service (BAaaS). BAaaS is an emergent service that provides individual, or organization, or information system, with the ability to share a wide range of analytical tools that can be available on the web or used by the smartphones.

BAaaS is gaining popularity in recent years and many giant companies such as Microsoft, Amazon, and eBay adopted it (Sun, Zou, & Strang, 2015). Depeige & Doyencourt (2015) argue further that leveraging BDA to better manage and deliver knowledge services increases the benefits of Knowledge as a Service (KaaS) and its underlying processes offered in the cloud environment. KaaS can be considered as an on-demand knowledge store that has the ability to search, analyze and restructure its knowledge resources using cloud-computing environment (Depeige & Doyencourt, 2015). Furthermore, Depeige & Doyencourt (2015) argue on the close relationship between BI/BD/BDA and Knowledge Management (KM). Depeige & Doyencourt (2015) highlight the evolution of BI analytics towards contextualized Knowledge Analytics (K-Analytics) that improve the capability to gain business value from data insights based on descriptive and predictive methods. Depeige & Doyencourt (2015) introduced actionable KaaS concept to induce valuable results.

Trends in Big Data Adoption

Amazon, Facebook, Google, Netflix, Dell, eBay, LinkedIn, Procter and Gamble, Target, Tesco, UPS, Walmart, and Zara are examples of organizations that have been successful at sustaining BDAC and setting the example (Walls & Barnard, 2020). The majority of these companies have born digital; they had a head step by digitizing all their operations. They have already adopted data-driven process as the source of the corporate strategy (Walls & Barnard, 2020).

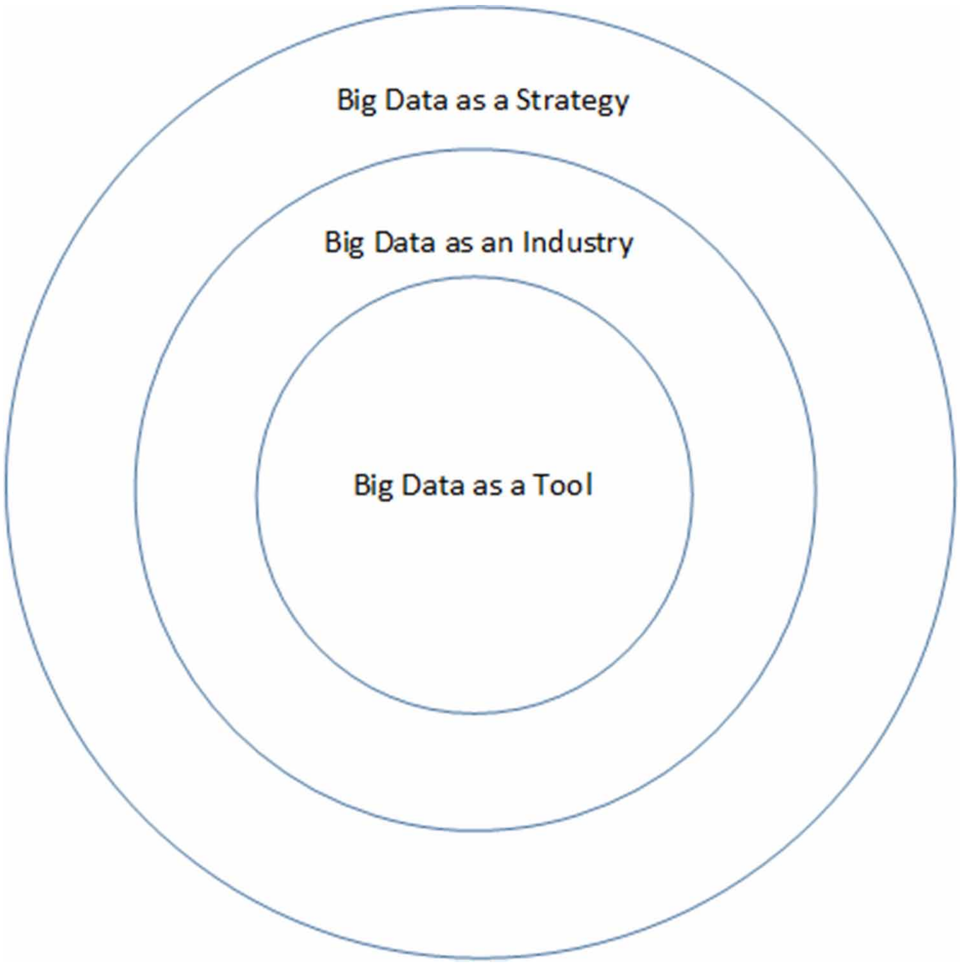
However, this is not the case of the majority of the current organizations that trying to adopt BDA, and sustainably utilize BD to its full potential and benefits. Scholars argued the surveys' results showing how it is difficult for organizations to understand how to leverage BD insights in order to create value (Erevelles, Fukawa, Swayne 2016; Walls & Barnard, 2020). Even though an organization may extract BD insights successfully, there is no guarantee that they are able to utilize these insights effectively (Erevelles, Fukawa, Swayne 2016; Walls & Barnard, 2020). Even more many organizations could not understand how BDAC will affect their business performance and competitive advantages, and this explains Erevelles et al. (2016) findings that more than 50% of big data initiatives do not achieve their targets.

Mazzei, & Noble (2017) presented a BD maturity framework that highlights how BD can be used as an evolutionary strategic management tool, not only an IT tool that can use data as a source for corporate strategies. The framework is based on three tiers: big data as a tool, as an industry, and as a strategic tool. Scholars used Mazzei, & Noble (2017) BD framework in their studies; e.g. Walls & Barnard (2020) utilized it to identify the success factors of BDAC on organizational performance. Our study will use this framework to differentiate between the organizations adopting BD initiatives, and highlight how deeply BD technologies are used by different companies and integrated in their internal processes (Figure 3).

Big Data as a Tool

Many organizations currently use BD initiatives to improve their core functions performance using its analytics technology (Mazzei, & Noble, 2017). For example, Volvo Cars Company implemented a new automatic fault monitoring system. Using the data collected from the sensors installed inside vehicles. This data, combined with the data collected from the maintenance workshops, and the customer analysis results obtained from the social media data analysis, this device is able to provide a high quality advisor for its customers (Sadovskyi, Engel, Heininger, Böhm, & Krcmar, 2014). Ford Cars Company constantly provides information regarding relevant car parameters in real time to the driver. Ford's engineers can use

Figure 3. Big Data Adoption Framework



this data to continuously improve the product or provide additional services, like location service to the next charging station (Bischof, Gabriel, Rabel, & Wilfinger, 2016). Starbucks, the famous coffee giant is using BDA with crowd sourcing to determine the success of any new location. It uses the information about the location, traffic, area demographic, and customer behavior to assess the location before opening any new store. Such analytics provides Starbucks with accurate estimation of the success rate of the new location (Satish & Yusof, 2017). Target proactively utilizes consumer insights from BDA to predict consumer behavior. Target is able to estimate if a shopper woman is pregnant and her due date weeks before other competitors. The company is able due to predictive analysis to enhance adaptive capability to influence the customer's purchases towards baby items, and capturing sales before competitors (Erevelles, Fukawa, Swayne 2016). Southwest Airlines developed a BD application that extracts insights from customer's conversation records using a speech-analytics tool. Insights results are used to improve performance, and facilitate its dynamic capabilities (Erevelles, Fukawa, Swayne 2016). Los Angeles city is applying the demand-responsive pricing for parking application based on BDA. The goal is to reach a steadily high utilization of the parking spaces at all times, considering the data feed from parking sensors, the weather forecasts, holidays, etc. This BD based application helps them maximize parking utilization, with best pricing (El-Darwiche, Koch, Meer, Shehadi, & Tohme, 2014). United Healthcare, a large health insurance company, is using BD for its customer satisfaction application. The recorded voice files from customer calls to call center are transformed into text formats, and then analyzed to extract meaning from text using natural language processing. This analysis process is able to identify any customer's dissatisfaction (Davenport, 2014).

Big Data as an Industry

Organizations at this level are using BD for creating new ventures specialized in acquisition, storage and analysis of companies' huge data, construction of BD infrastructure, and development of all related software (Mazzei, & Noble, 2017). For example, Pivotal is using BD as an innovative industry. It provides "platform as a service" to allow clients to build their applications in its cloud (Mazzei, & Noble, 2020). Finning, a Caterpillar dealer, has transformed from a traditional repair service to a provider of support for customers' machines through predictive and prescriptive BDA. Customer experience insights enable Finning to track a machine's location, prevent premature failure, prolong service life, minimize downtime, increase operator efficiency, reduce the cost of repair, and recommend solutions (Holmlund, Van Vaerenbergh, Ciuchita, Ravald, Sarantopoulos, Villarroel-Ordenes, & Zaki, 2020). Netflix is a success story using BD sensing and seizing practices. Netflix created a new TV series, House of Cards, based on BDA that powerfully revealed viewers tastes such as favorites actors and actresses. This new innovative series brought Netflix millions as new revenues. This success showcase provides evidence supporting the relationship between market (customer) orientation and BD capability (Lin & Kunnathur, 2019; Akter, Fosso Wamba, Gunasekaran, Dubey, & Childe, 2016). Spotify, a streaming provider, created a personalized experience for each customer. Spotify capitalized on descriptive and predictive BDA to generate customer experience behavioral insights (i.e., knowledge on listening habits) and design highly personalized touchpoints. Spotify sent each customer a personalized email with information about their listening habits. These actions allowed Spotify to create personalized touchpoints in each customer's journey by generating custom playlists (Holmlund, Van Vaerenbergh, Ciuchita, Ravald, Sarantopoulos, Villarroel-Ordenes, & Zaki, 2020). Uber is the best showcase of the link between entrepreneurial orientation and BD capability. It is due to the entrepreneurial insights of Uber creators that helped them capturing the business value behind the real-time flow of digital data streams (Lin & Kunnathur, 2019).

Big Data as a Strategy

Organizations at this level reveal the new strategic thinking of using BD as a source of innovative business models of markets and products, and a driver of competitive strategy (Mazzei, & Noble, 2017). Inside these organizations, new leaders' innovative thinking concentrates on data flows rather than data stocks. They are able to create new ecosystems based on the data they accumulate and the increase of data flow. These learning organizations evolve dynamically; based on the uncovered trends in their data analysis. Organizations at this level have the ability to increase opportunities to diversify and expand into new markets (Walls & Barnard, 2020; Mazzei, & Noble, 2017; El-Darwiche, Koch, Meer, Shehadi, & Tohme, 2014). Amazon is an exceptional case where a company is using BD at all levels, as a tool, as an innovative industry, and as a corporate strategy (Mazzei, & Noble, 2020). Amazon is the best case showing a business model transformation based on Big-Data-Driven industry (Bischof, Gabriel, Rabel, & Wilfinger, 2016). Started as a traditional bookseller, it was evolved to one of the largest online traders.

The company's platform was opened to other traders providing them access to their customer database and logistics network. Amazon is currently transformed its business model into a full service provider based mainly on BD (Mazzei, & Noble, 2020; Bischof, Gabriel, Rabel, & Wilfinger, 2016). Amazon restructures its distribution strategy in order to gain greater value through radical innovation. Amazon is able to predict when a customer will make a purchase, and start shipping products to nearest hub before the customer submits the order (Erevelles, Fukawa, Swayne 2016). Currently, 35% of purchases are generated from personalized purchase recommendations to customers based on BDA (Fosso Wamba, Gunasekaran, Akter, Ren, Ji-fan, Dubey, & Childe, 2017). Additionally, 30% of sales were newly generated from the new predictive technique called 'collaborative filtering' that generate "you might also want" prompt for each product bought or visited based on customer data (Akter, Fosso Wamba, Gunasekaran, Dubey, & Childe, 2016). Apple is another best showcase of a company using big data as a strategy (Mazzei, & Noble, 2017). Starting initially from a personal computer manufacturer, the company expanded its ecosystem data flows by collecting data in digital music, videos, telecommunications and other markets. Using BD as their corporate strategy, Apple was able to tackle and expand to new markets, including wearable, automobiles and mobile payment services. All of which are strategically integrated to the core company's platform (Mazzei, & Noble, 2017). John Deere, Agricultural equipment manufacturer, capitalized on BDA and equipped its machines with sensors that allowed customers to access and analyze their machine data, benchmarking it against other machines and combining it with historical data in real time and for free. Thus, John Deere introduced new touchpoint design that changed its customers' entire journey. Currently, myJohnDeere.com platform is opened to suppliers, retailers, and software developers. John Deere transitioned from a manufacturing business model to a platform-centric model, thus achieved innovation and revolutionized the agriculture industry (Holmlund, Van Vaerenbergh, Ciuchita, Ravald, Sarantopoulos, Villarroel-Ordenes, & Zaki, 2020).

FUTURE RESEARCH DIRECTIONS

Although BDA is a new research challenge, it is becoming a subject of growing importance. However, BD research has a relatively short history, starting in 2011 from only 38 studies listed in the Science Citation Index Expanded (SCIE), Social Science Citation Index (SSCI), Arts & Humanities Citation Index (AHCI), and Emerging Sources Citation Index (ESCI). The number of studies was increased to 3890 studies in 2017 (Jin, & Kim, 2018).

This paper outlines some avenues for future researches in the arena of BD; integration of BD with strategic management is an important research direction. A fundamental question remains: To what extent strategic management theories can be adopted to provide organizations with the ability to best adapt with BD initiatives. Big Data Maturity Model is another search direction, although different models were suggested, there is still a room for improvement, especially from best practices viewpoint.

CONCLUSION

BI was characterized by flexibility and adaptability in which traditional applications are not able to deal with. Traditional process modeling requires a lot of documentation and reports and this makes traditional methodology unable to fulfill the dynamic requirements of changes of our high-speed, high-change environment. BI main drawbacks was mainly related to data management issues, especially when dealing with huge data amount, and unstructured data types.

Technological development in data storage and processing make it possible to handle exponential increases in data volume in different type format. Hence, it was the cornerstone behind BD revolution. BD has become a source for innovation and competitive advantage by transforming decision making and leading to new strategic models. Decision-making process was redefined to incorporate the new strategic effects of BD & BDA concepts.

Borderlines between BI, BD and BDA still unclear for many companies. This paper provided a comprehensive view about all these concepts, the interrelationship between them, the new created organizational capabilities, and the different levels of BD adoption. Companies already integrated BI in their internal processes can extend their technological infrastructure and skills, and restructure their processes to gain value from BI/BD/BDA integration, improve their competitive advantages, and enhance organizational performance.

This paper concludes that analytics capability is the core power of BI/BD/BDA. BD (including BDA) is an extension of BI. It is worth noting that BD is more than a technology, and to be fully effective, it should be incorporated into corporate strategy. Arguably, BD affects organizational culture; it converts firms to become data and evidence-based organizations. Most notably, BD enables organizations to create entirely new innovative products, and new business models.

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KEY TERMS AND DEFINITIONS

Big Data (BD): Is a holistic approach to manage process and analyze the 7 V's (i.e., volume, variety, velocity, veracity, value, valence, and variability) in order to create actionable insights for sustained value delivery, measuring performance, establishing competitive advantages, and becoming a source of innovation.

Big Data Analytics (BDA): Is the process of collecting, organizing, and analyzing big data to discover patterns, knowledge, and intelligence as well as other information within the big data.

Big Data Analytics Capability (BDAC): Is the organizational capabilities that can enable firms to analyze their huge data with nontraditional methods using big data tools and techniques; hence, producing insights that enable data-driven decision-making process.

Business Intelligence (BI): Is an umbrella term that combines architectures, tools, databases, applications, practices, and methodologies. It is the process of transforming various types of business data into meaningful information that can help, decision makers at all levels, getting deeper insight of business.

Cloud Computing (CC): Is the result of evolutions of distributed computing technologies, enabled by advances in fast and low-cost network, commoditized faster hardware, practical high performance virtualization technologies, and maturing interactive web technologies.

Data Mining (DM): Is the process of discovering interesting information from the hidden data that can either be used for future prediction and/or intelligently summarizing the details of the data.

Data Warehouse (DW): Is a physical repository where relational data are specially organized to provide enterprise-wide, and cleansed data in a standardized format.

Knowledge Management (KM): Is the acquisition, storage, retrieval, application, generation, and review of the knowledge assets of an organization in a controlled way.