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της

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MASTER'S THESIS

Of

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BID DATA ANALYTICS STRATEGY: A LITERATURE REVIEW

Supervisor : Associate Professor George Lekakos

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Βεβαίωση εκπόνησης Διπλωματικής εργασίας

«Δηλώνω υπεύθυνα ότι η συγκεκριμένη μεταπτυχιακή εργασία για τη λήψη του μεταπτυχιακού τίτλου σπουδών του ΠΜΣ στη Διοικητική Επιστήμη και Τεχνολογία του Τμήματος Διοικητικής Επιστήμης και Τεχνολογίας του Οικονομικού Πανεπιστημίου Αθηνών έχει συγγραφεί από εμένα προσωπικά και δεν έχει υποβληθεί ούτε έχει εγκριθεί στο πλαίσιο κάποιου άλλου μεταπτυχιακού ή προπτυχιακού τίτλου σπουδών στην Ελλάδα ή το εξωτερικό. Η εργασία αυτή έχοντας εκπονηθεί από εμένα, αντιπροσωπεύει τις προσωπικές μου απόψεις επί του θέματος. Οι πηγές στις οποίες ανέτρεξα για την εκπόνηση της συγκεκριμένης διπλωματικής αναφέρονται στο σύνολό τους, δίνοντας πλήρεις αναφορές στους συγγραφείς, συμπεριλαμβανομένων και των πηγών που ενδεχομένως χρησιμοποιήθηκαν από το διαδίκτυο».

ΤΖΙΤΖΙΡΗ ΙΩΑΝΝΑ

Φοιτήτρια MSc στη Διοικητική Επιστήμη και Τεχνολογία

Περίληψη

Η αναλυτική δεδομένων αναδεικνύεται ως ένα μεγάλης σημασίας θέμα λόγω του υψηλού επιχειρησιακού και στρατηγικού δυναμικού της ιδιαίτερα στη δημιουργία επιχειρηματικής αξίας. Αρχικά, παρουσιάζονται και εξηγούνται τα χαρακτηριστικά και οι προκλήσεις που προκύπτουν από τα μεγάλου όγκου δεδομένα, η αναλυτική δεδομένων και βασικές θεωρίες που την συνδέουν με την εταιρική επίδοση. Στη συνέχεια, με βάση την βιβλιογραφία παρουσιάζονται οι τομείς στους οποίους η αναλυτική δεδομένων μπορεί να αξιοποιηθεί και πώς μπορεί να βελτιώσει την επίδοση μίας επιχείρησης. Έπειτα, περιγράφονται σύμφωνα με την υπάρχουσα βιβλιογραφία οι συνθήκες με τις οποίες μία επιχείρηση μπορεί να εξασφαλίσει τα πιθανά οφέλη από τις επενδύσεις της στην αναλυτική δεδομένων. Τέλος, παρέχονται συμπεράσματα και προτάσεις για περαιτέρω έρευνα.

Λέξεις κλειδιά: αναλυτική δεδομένων, εταιρική επίδοση, πεδία εφαρμογής αναλυτικής δεδομένων, επιχειρηματική αξία

Abstract

Data analytics emerges as a major issue because of its high operational and strategic potential, particularly in creating business value. Initially, the concept, characteristics and challenges arising from the bulk of data, data analytics and basic theories that link it to firm performance are presented and explained. Subsequently, based on the literature, the areas in which the data analytics can be exploited are presented and how it can improve organizational performance. Then, according to the existing literature, the conditions under which an enterprise can secure the potential benefits of its investment in the analytical data are described. Finally, conclusions and proposals for further research are provided.

Keywords: big data analytics, firm performance, big data application fields, business value

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1. Introduction

Big data analytics is emerging as a hot topic among scholars and practitioners due to its high operational and strategic potential, especially in generating business value. Some scholars and practitioners suggest that BDA is the ‘fourth paradigm of science’ (Strawn, 2012, p.34), a ‘new paradigm of knowledge assets’ (Hangstrom, 2012, p.2), or ‘the next frontier for innovation, competition and productivity’ (Manyika et al., 2011, p.1).

1.1. Objectives and Contribution

The purpose of the thesis is the literature review aiming at the identification of impact of big data in various fields, thus enhancing firms’ performance and the factors to be taken into account for converting big data investments into value.

1.2. Research Method

The process followed to conduct the literature review is described as follows:

The first step was the definition of the research question which is the purpose of thesis as presented above. The research question guided the search strategy, the selection of articles and the inclusion criteria.

Subsequently, the search strategy started by forming search strings (keywords). The next step was the definition of the combinations of keywords to use in the searches of articles. The first combination was determined to capture articles about big data and firm performance. More specifically, the first term was ‘big data’ and the second was ‘analytics’ or ‘intelligence’ or ‘competitive advantage’ or ‘firm performance’ or ‘company performance’ or ‘organizational performance’ or ‘enterprise performance’ or ‘business value’. The second combination was applied to capture articles about big data employment in specific fields, the enablers and inhibitors of successful utilization of big data. In particular, the first term was ‘big data’ and the second was ‘innovation’ or ‘decision making’ or ‘marketing’ or ‘supply chain’ or ‘procurement’ or ‘inventory management’ or ‘logistics’ or ‘transportation’ or ‘business process’ or ‘strategy’ or ‘leadership’ or ‘enablers’ or ‘inhibitors’ or ‘success factors’ or ‘successful implementation’ or ‘successful adoption’ or ‘governance’. After the exclusion of articles that appeared in both searches, the total number identified was 130.

After reading the titles, abstracts and keywords of the studies, they were assessed based on their relevance to the literature review. 95 papers were omitted. The remaining papers were fully read. None of these was excluded as they were all identified as capable of responding to the defined research question.

The final steps of the literature review were the in-depth reading and analysis of the papers to categorize them based on their scope and identify the contributions and the gaps for future research.

1.3. Structure of the Thesis

This thesis is structured as follows: following this introduction (section 1), a background of the main concepts is provided (Section 2). In section 3 big data application fields are presented, while Section 4 describes the conditions under which big data investments can be turned into value. Lastly, the conclusion (Section 5) explains the implications of this literature review for theory and practice and provides suggestions for further research.

2. Background of the Study

2.1. Big Data Challenges

In their literature review, Sivarajah, Kamal, Irani & Weerakkody (2016) define the different types of big data challenges confronted by organizations.

Data challenges

Data challenges are the group of the challenges that are related to the characteristics of the data itself. Seven characteristics were found which are described as follows:

Volume: refers to the huge amount of data that are being generated. Generally, there have been four significant trends that have caused a considerable increase in data generation. More specifically, they are: the growth in traditional transactional databases, the increase of multimedia content, the growth of the 'Internet of Things' and the growing popularity of social media.

The growth in traditional transactional databases is highly connected with the fact that organizations are collecting data with greater granularity and frequency in order to deal with the increasing level of competition, increasing turbulence in the business environment and the growing expectations of customers. All of these factors necessitate organizations to react rapidly and with maximum flexibility to the changes taking place and adjust to them. In order to achieve this, they are forced to conduct more and more detailed analysis concerning marketplaces, competition and the behavior of consumers. The second trend is connected with the rapid increase in the use of multimedia in the industries of the contemporary economy. The third trend which has caused a growth in the amount of data being generated is the development of the phenomenon called "The Internet of Things", where the number of devices that communicate with each other without any human interference is increasing at a fast pace. As devices equipped with various sensors or actuators, they collect and send huge amounts of data. Social media is the fourth extremely significant source of the increase of data.

Variety: The enormous volume of data that are being generated is not consistent nor does it follow a specific template or format. On the contrary, it is captured in diverse forms and diverse sources (Chen, Chiang & Storey, 2012; Chen et al., 2013). According to Syed et al. (2013), big data is made of structured and unstructured information. The most common form of structured data is a database where specific information is stored based on methodology of columns and rows. This type of information is searchable, efficiently organized for human readers and secure and easy to analyze. However, analysis of unstructured data is a big challenge for all companies as they cannot be aligned into columns and rows. Unstructured data can be images, videos, web pages, text files, e-mails. These different forms and quality of data clearly indicate that heterogeneity is a natural property of big data and it is a big challenge to comprehend and manage such data (Labrinidis & Jagadish, 2012).

Veracity: Akerkar (2014) and Zicari (2014) refer veracity to as coping with the biases, doubts, imprecision, fabrications and displaced evidence in the data. Veracity feature measures the accuracy of data and its potential use for analysis (Vasarhelyi, Kogan & Tuttle, 2015). For example, every customer opinion on different social media networks and web is different and unclear in nature as it involves human interaction (Sivarajah, Irani, & Weerakkody, 2015). The necessity to deal with inaccurate and ambiguous data is another facet of big data which is addressed using tools and analytics developed for management and mining of unreliable data (Gandomi & Haider, 2015).

Velocity: The challenge of velocity comes with the requisite to manage the high influx rate of non-homogenous data which results in creating new data or updating existing data (Chen et al., 2013). This mainly applies to those datasets that are generated through large complex networks including data generated by the proliferation of digital devices which are positioned ubiquitously resulting in driving the need for real time analytics and evidence based planning (Lu, Zhu, Liu, Liu, & Shao, 2014).

Variability: Variability concerns how insight from media constantly changes as the same information is interpreted in a different way, or new feeds from other sources help to shape a different outcome. Variability is also related in performing sentiment analysis. For example, in the same tweets a word can have a totally different meaning. In order to perform a proper sentiment analysis advocates assert that algorithms need to be able to understand the context and be able to decipher the exact meaning of a word in that context (Zhang, Hu et al., 2015).

Visualization: Visualization can be described as interpreting the patterns and trends that are present in the data (Seddon and Currie 2017). Visualizing data is about representing key information and knowledge more instinctively and effectively using different visual formats such as in pictorial or graphical layout (Taheri, Zomaya, Siegel, & Tari, 2014).

Value: Big data researchers consider value an essential feature, as somewhere in that data there is valuable information, though most of the pieces of data independently may seem insignificant (Zaslavsky, Perera, & Georgakopoulos, 2012). According to Abawajy (2015) organizations are still faced with challenges of storing, managing and predominantly extracting value from the data in a cost effective manner.

Process challenges

Due to the characteristics of big data, organizations have to encounter challenges while processing and analyzing the data that is from capturing the data to interpreting and presenting the end results. As large datasets are usually non-relational or unstructured, thus processing such semi-structured data sets at scale poses a significant challenge (Kaisler, Armour, Espinosa, & Money, 2013).

Data Acquisition and Warehousing: This challenge is related to acquiring data from diverse sources and storing for value creation purpose. The integral complexity of big data and exponentially growing demands develop unprecedented problems in big data engineering such as data acquisition and storage (Wang & Wiebe, 2014). The latter argument is supported by Paris, Donnal, and Leeb (2014) who assert that one of the prime barriers to the analysis of big data arises from a lack of data provenance, knowledge and discrepancies of scale inherent in data collection and processing. This further restricts the speed and resolution at which data can be captured and stored. As a result, this affects the capability to excerpt actionable information from the data (Chen & Zhang, 2014). In order to capture related and valuable information, smart filters are required that should be robust and intelligent to capture useful information and discard useless that contains imprecisions or inconsistencies. For the latter, efficient analytical algorithms are required to understand the provenance of data and process the vast streaming data and to reduce data before storing (Zhang, Hu et al., 2015;Zhang, Liu et al., 2015).

Data Mining and Cleansing: This challenge relates to extracting and cleaning data from a collected pool of large scale unstructured data. Advocates of big data and big data analytics perceive that in identifying a better way to mine and clean the big data can result in big impact and value (Chen, Chen et al., 2012). Due to its strident, vibrant, diverse, interrelated and unreliable features, the mining, cleansing and analysis proves to be very challenging (Chen et al., 2013). In order make use of this huge data in a meaningful way, there is a need to develop an extraction method that mines out the required information from unstructured big data and articulate it in a standard and structured form that is easy to understand. According to Labrinidis and Jagadish (2012) developing and maintaining this extraction method is a continuous challenge.

Data Aggregation and Integration: This process challenge relates to aggregating and integrating clean data mined from large unstructured data. Big data often aggregates varied online activities such as tweets and likes on Facebook that essentially bear diverse meanings and senses (Edwards & Fenwick, 2015). This characteristically amorphous data naturally lacks any binding information. Aggregating these data evidently goes beyond the abilities of current data integration systems (Carlson et al., 2010). According to Karacapilidis, Tzagarakis, and

Christodoulou (2013), the availability of data in large volumes and diverse types of representation, smart integration of these data sources to create new remains a key challenge. Halevy, Rajaraman, and Ordille (2006) assert that the indecision and provenance of data are also a major challenge for data aggregation and integration. Another challenge relates to aggregated data in warehouse, Lebdaoui, Orhanou, and Elhajji (2014) report that to enable decision systems to efficiently respond to the real world's demands, such systems must be updated with clean operational data.

Data Analysis and Modelling: Once the data has been captured, stored, mined, cleaned and integrated, comes the data analysis and modelling for big data. Outdated data analysis and modelling centers around solving the intricacy of relationships between schema-enabled data. As big data is often noisy, unreliable, heterogeneous, dynamic in nature, these considerations do not apply to non-relational, schema-less databases (Shah et al., 2015). From the perspective of differing between big data and traditional data warehousing systems; Kune, Konugurthi, Agarwal, Chillarige, and Buyya (2016) report that although these two have similar goals; to deliver business value through the analysis of data, they differ in the analytics methods and the organization of the data. Consequently, old ways of data modelling no longer apply due to the need for unprecedented storage resources/capacity and computing power and efficiency (Barbierato et al., 2014). Thus, there is a need for new methods to manage big data for maximum impact and business value. It is not merely knowing about what is currently trendy, but also need to anticipate what may happen in the future by appropriate data analysis and modelling (Chen et al., 2013).

Data Interpretation: This process is relatively similar to visualizing data and making data understandable for users that is the data analysis and modelling results are presented to the decision makers to interpret the findings for extracting knowledge (Simonet, Fedak, & Ripeanu, 2015). The growth and multiplicity of unstructured data have intensely affected the way people process and interpret new knowledge from these raw data. As much of these data both instigate and reside as an online resource, one open challenge is defining how Internet computing technological solutions have evolved to allow access, aggregate, analyze, and interpret big data (Bhimani & Willcocks, 2014). Another challenge is the shortage of people with analytical skills to interpret data (Phillips-Wren & Hoskisson, 2015).

Management challenges

Challenges also encountered while accessing, managing and governing the data. Organizations and businesses need to ensure that they have a robust security infrastructure that enables employees and staff of each division to only view relevant data for their department. Moreover, there must be some standard privacy laws that may govern the use of such personal information and strict observance to these privacy regulations must be applied in the data warehouse.

Privacy: Data warehouses store massive amounts of sensitive data such as financial transactions, medical procedures, insurance claims, diagnosis codes, personal data, etc. Consequently, big data poses big privacy concerns and how to preserve privacy in the digital age is a prime challenges. Huge investments have been made in big data projects to streamline processes; however, organizations are facing challenges in managing privacy issues, and recruiting data analysts, thus hindering organizations in moving forward in their efforts towards leveraging BD (Krishnamurthy & Desouza, 2014). In a smart city environment where sensory devices gather data on citizen activities that can be accessed, several government and security agencies pose significant privacy concerns (Barnaghi et al., 2013). Among such privacy related challenges, location-based information being collected by big data applications and transferred over networks is resulting in clear privacy concerns (Yi et al., 2014). For example, location-based service providers can identify subscriber by tracking their location information. Then there is the challenge of protecting privacy – Machanavajjhala and Reiter (2012) report that failure to protect citizens' privacy is illegal and open to relevant government oversight bodies.

Security: Security is a major issue and is identified by Lu et al. (2014) who argue that if security challenges are not appropriately addressed then the phenomenon of big data will not receive much acceptance globally. Among the several big data related security challenges are the distributed nature of large BD which is complex but equally vulnerable to attack (Yi et al., 2014), malware has been an ever growing threat to data security (Abawajy, Kelarev, & Chowdhury, 2014), lack of adequate security controls to ensure information is resilient to altering (Bertot, Gorham, Jaeger, Sarin, & Choi, 2014), lack of sophisticated infrastructure that ensures data security such as integrity, confidentiality, availability, and accountability, and data security challenges become magnified when data sources become ubiquitous (Demchenko, Grosso, De Laat, & Membrey, 2013).

Data Governance: As the demand for big data is constantly growing, organizations perceive data governance as a potential approach to warranting data quality, improving and leveraging information, maintaining its value as a key organizational asset, and support in attaining insights in business decisions and operations (Otto, 2011). According to Intel IT Centre (2012), IT managers highly support the presence of a formal big data strategy since the issue of data governance for describing what data is warehoused, analyzed, and accessed is termed as one of the three top challenges they face. du Mars (2012) state that a significant challenge in the process of governing big data is categorizing, modelling and mapping the data as it is captured and stored, mainly due to the unstructured and complex nature of data. Moreover, effective big data governance is essential to ensure the quality of data mined and analyzed from a pool of large datasets (Hashem et al., 2015).

Data and Information Sharing: Sharing data and information needs to be balanced and controlled to maximize its effect, as this will facilitate organizations in establishing close connections and harmonization with their business partners (Irani, Sharif, Kamal, & Love, 2014). However, where organizations store large scale datasets that have potential analysis challenges, it also poses an overwhelming task of sharing and integrating key information across different organizations (OSTP, 2012). Al Nuaimi et al. (2015) also state that sharing data and information between distant organizations or departments is a challenge. For instance, each organization and their individual departments typically own a disparate warehouse of sensitive information and several departments are often reluctant to share their patented data governed by privacy conditions. According to Khan, Uddin, and Gupta (2014) the challenge here is to ensure not to cross the fine line between collecting and using big data and guaranteeing user privacy rights.

Cost/Operational Expenditures: The constantly increasing data in all different forms has led to a rising demand for big data processing in sophisticated data centers. These are generally dispersed across different geographical regions to embed resilience and spread risk, for example Google having 13 data centers in eight countries spread across four continents (Gu, Zeng, Li, & Guo, 2015). The significant resources have been allocated to support the data intensive operations which leads to high storage and data processing big costs (Raghavendra, Ranganathan, Talwar, Wang, & Zhu, 2008). Researchers assert that cost minimization is an emergent challenge (Irani, Ghoneim, & Love, 2006; Irani, 2010), with Gu et al., 2015 explaining the challenges of processing BD across geo-distributed data centers. Advocates of BD search for cost-effective and efficient ways to handle the massive amount of complex data (Sun, Morris, Xu, Zhu, & Xie, 2014). The cost of data processing and other operational expenditures of the data center are a sensitive issue that may also impact in the way organizations adopt and implement technological solutions (AlNuaimi et al., 2015).

Data Ownership: Besides privacy, Web (2007) asserts that ownership of data is a complex issue while sharing real time data. Kaisler et al. (2013) also claim that data ownership presents a critical and continuing challenge, specifically in the social media context such as who owns the data on Facebook, Twitter or MySpace– are the users who update their status or tweet or have any account in these social networks (Sivarajahetal., 2015; Sivarajah, Irani, & Jones, 2014). It is generally perceived that both view they own the data. Kaisler et al. (2013) argues that this dichotomy still needs to be settled. With ownership arise the issue or controlling and ensuring its accuracy. For instance, Web (2007) states that sensor data is too sensitive and can result in mounting errors – this may further result in capturing and revealing inconsistent data –but then who owns that data. Data ownership is a much deeper social issue. These concerns are beyond the focus on several applications, for example SensorMaps by Web (2007) requires more research since they may have deep implications.

2.2. Business Intelligence and Analytics

Business Intelligence and analytics have become the significant research area in the domain of management information systems in the last years (Chen, Chiang & Storey, 2012). The roots of BI&A originate from decision support systems, which first emerged in the early 1970s when managers used computer applications to model business decisions.

Business intelligence is defined as the methodologies, systems and applications for collecting, preparing and analyzing data to provide information helping decision makers. In other words, BI systems are data-driven decision making systems, while business analytics are the techniques, technologies, systems and applications that are used to analyze critical business data for supporting them to understand their business environment and take business decisions on time. The power of business analytics is to streamline vast amounts of data to enhance its value, while business intelligence mainly concentrates historical data in graphs and data table reports as a way to provide answers to queries without streamlining data and enhancing its value.

More recently, the term business intelligence and analytics (BI&A) has been proposed (Chen et al. 2012) to reflect both the growing importance of the analytical components of BI systems and the shift from reporting-centric capabilities to analysis-centric capabilities in BI applications (Sallam et al. 2014).

BI&A research is often centered on BI&A technologies. More specifically, the key BI&A technologies include: data warehousing, data mining, and OLAP (Olszak & Ziemba, 2006). In the last years, new techniques, such as: web mining, opinion mining techniques, mobile mining techniques and semantic processing are applied in BI&A applications. Such applications, focused mainly on processing of semi-structured or unstructured data that originate from internet and social media. The most recent applications are responsible for collecting and analyzing data from various mobile devices (Chen, Chiang & Storey, 2012; Olszak, 2013).

In addition, a significant portion of the BI&A literature is devoted to the development, evaluation, and application of various algorithms and analytical techniques (Sidorova et al. 2013).

The types of analytics found in the literature are presented as follows (Sivarajah, Kamal, Irani, Weerakkody, 2016):

Descriptive analytics

Descriptive analytics are the simplest form of big data analytics method, and involves the summarization and description of knowledge patterns using simple statistical methods, such as mean, median, mode, standard deviation, variance, and frequency measurement of specific events in BD streams (Rehman et al., 2016). Often, large volumes of historical data is used in descriptive analytics to identify patterns and create management reports that is concerned with modelling past behavior (Assunção et al., 2015). Watson (2014) asserts that descriptive analytics, such as reporting, dashboards, scorecards, and data visualization, have been widely used for some time, and are the core applications of traditional business intelligence. Descriptive analytics are considered backward looking and reveal what has already occurred. Spiess, T'Joens, Dragnea, Spencer, and Philippart(2014) highlights root cause analysis and diagnostics are also form of descriptive analysis which involve both the passive reading and interpretation of data, as well as initiating particular actions on the system under test, and reading out the results. They discuss that root cause analysis is an elaborate process of continuous digging into data, and correlating various insights such as to determine the one or multiple fundamental causes of an event (Spiess et al., 2014). Another form of descriptive analysis, pointed out by Banerjee, Bandyopadhyay, and Acharya(2013) is the use of dashboard sort of application when a business routinely generates different metrics including data to monitor a process or multiple processes across times.

Predictive analytics

This analytics is concerned with forecasting and statistical modelling to determine the future possibilities based on supervised, unsupervised, and semi-supervised learning models (Joseph & Johnson, 2013; Rehman et al., 2016; Waller & Fawcett, 2013). Gandomi and Haider (2015) asserts the need to develop new solutions for predictive analytics for structured big data. Predictive analytics are principally based on statistical methods and seeks to uncover patterns and capture relationships in data. Gandomi and Haider (2015) categorized predictive analysis into two groups – regression techniques and machine learning techniques. The authors highlight that some approaches, such as moving averages, attempt to identify historical patterns in the outcome variable and extrapolate them to the future. Others, such as linear regression, seek to capture the interdependencies between outcome variable(s) and explanatory variables, and use them to make predictions. Hasan, Shamsuddin, and Lopes (2014) proposed a machine learning big data framework that envisaged the broad picture of machine learning in dealing with big data problems. In sum, predictive analytics aims to predict the future by analyzing current and historical data.

Prescriptive analytics

This type of analytics is performed to determine the cause-effect relationship among analytic results and business process optimization policies. Therefore, organizations optimize their business process models based on the feedback provided by predictive analytic models (Bihani & Patil, 2014). Although difficult to deploy, prescriptive analytics contribute to handling the information shift and the continuous evolution of business process models (Rehman et al., 2016). There are very limited examples of good prescriptive analytics in the real world. One of the reasons for this shortage is that most databases are constrained on the number of dimensions that they capture (Banerjee et al., 2013). Therefore, the analysis from such data provides, at best, partial insights into a complex business problem. Few initial studies have applied the simulation optimization methods to the big data analytics. For instance, Xu, Zhang, Huang, Chen, and Celik (2014) proposed a framework called multi- fidelity optimization with ordinal transformation and optimal sampling. In general, prescriptive solutions assist business analysts in decision making by determining actions and assessing their impact regarding business objectives, requirements, and constraints. For example, what if simulators have helped provide insights regarding the plausible options that a business could choose to implement in order to maintain or strengthen its current position in the market.

2.3. Big Data Analytics Business Value

Besides challenges that organizations have to face when using big data, there are significant benefits that can reap.

Grover, Chiang, Liang, Zhang (2018) assert that big data analytics can create value by enhancing organizational performance, improving the effectiveness, efficiency and productivity of business processes, facilitating product and service innovation and delivering a better customer experience resulting in higher customer satisfaction and retention.

According to Raguseo, Vitari, (2018), there are four different forms of business value that firms can create from big data analytics investments: transactional, strategic, transformational and informational. Transactional value refers to the ability of big data analytics solutions to provide operational benefits, such as a reduction in operating costs, enhancement of employee productivity or savings in supply chain management. Strategic value refers to the enhancement of a company’s offer, for example, in terms of customer service or product innovations.

Transformational value measures the capability of an organization to change in order to take advantage of business opportunities or to transform its business model. Informational value, refers to an organization's ability to improve the flow of information, which in turn enables faster and easier access to data, and provides data in more useable formats.

Grover, Chiang, Liang, Zhang (2018) proposed six distinct mechanisms that mediate the linkage between big data analytics and value targets. According to them, value can be created through transparency and access, discovery and experimentation, prediction and optimization, customization and targeting, learning and crowdsourcing and continuous monitoring and proactive adaptation.

Manyika et al. (2011) also identified five key ways in which big data creates value for organizations which are analyzed as follows:

Transparency is created by integrating data and making it more easily accessible to all relevant stakeholders. All data that exist inside and outside the company become available in one place, so the company can establish one version of the truth. In addition, employees can easily find data which they need in one location, which consequently leads to savings in time and effort and enhancement of transparency.

Organizations can also create value through experimentation in order to identify different needs of customers and to create more custom products and services. Companies are now able to collect more detailed data about customers, their opinions and attitudes about products and services. Using different analytical techniques, companies can examine the effects of certain improvements in products and services.

Another way in which big data crates value is through identification of different customer segments in order to adjust products and services according to their needs and requirements. By creating different customer segments, companies gain a clearer picture of how they can meet customer needs better, and thus have a basis not only for improvement of existing products and services, but for the creation of new ones. Segmentation may be based on the large number of different criteria – income, age, location, buying habits, etc. (Kiron et al., 2011).

Big data can also support decision making process with automated algorithms. Sophisticated software has the possibility to improve the decision making process with automated algorithms which automatically analyze collected data and initiate corrective actions. The application of controlled experiments to test hypotheses and analyze the results of the decisions made, can significantly improve the decision making process (McGuire et al., 2012). Many authors pointed out that one of the significant changes is a shift from intuitive decision making to data driven decision making (Provost & Fawcett, 2013; Minelli et al., 2014).

Finally, big data can facilitate improvement of existing products and services and the introduction of new ones. By identifying certain relationships in data, companies can realize important facts about products and services. The results of the analysis can be a new product, service, improvement of existing product or service, a new approach to pricing, etc. (Davenport, 2014).

2.4. BDA and Theoretical Perspectives

A number of theoretical perspectives have been employed to guide investigations of the role of BI&A in organizations and the relationship between BI&A and organizational outcomes, including the information processing theory, the contingency theory, the service dominant logic, the resource based view (RBV) of the firm and the dynamic capabilities perspective.

Information processing theory, commonly used in investigations of the role of BI&A in organizations, is concerned with human information processing and postulates a relationship between problem space characteristics and information processing needs (Simon 1978). Although it has informed a number of BI&A studies that examine the link between BI&A and organizational benefits from a decision making perspective (Isik et al. 2013; Rouibah and Ould-ali 2002), it does not directly deal with the issue of organizational performance. Thus, studies grounded in this perspective typically do not extend beyond intermediary benefits of BI&A such as improved decision-making, speed to insight, and environmental awareness. Although valuable, such research does not directly test the mechanism through which these intermediary benefits influence firm performance.

Contingency theory states that organizations are open systems that constantly interact with their environment and adapt to different environmental pressures (Lawrence & Lorsch, 1973). The specific theory can be applied to understand how big data can help organizations to adapt to environmental conditions (Waller & Fawcett, 2013). It can also help verify the adaptation process required to compete and survive in the new reality of abundant data.

Service Dominant logic is a theory that explains value co-creation between firms and customers (Vargo & Lusch, 2004, 2008). Big data platforms represent an important channel for companies to co-create value with customers. Such technologies enable organizations to exercise a service-dominant strategy, by allowing collection of customer data, superior communication with customers, and effective response to changes (Xie et al., 2016).

The resource based view argues that acquiring, configuration, reconfiguration and developing of available resources are critical factors for taking the competitive advantage and enhancing firm performance (Barney, 1991; Cosik, Shankes, & Maynard, 2012; Wade & Hulland 2004). According to RBV in order to provide sustainable competitive advantage, resources should be: valuable, inimitable, rare and non-substitutable.

Resources are valuable when they enable a firm to enhance net revenues and reduce net costs (Barney and Arikan, 2001). Second, the rare dimension indicates that the resources are possessed by a small number of firms to achieve competitive advantages. Third, the imperfectly imitable dimension suggests that firms cannot directly copy or substitute such resources because they are costly to imitate.

Furthermore, resource based theory believes in achieving sustained competitive advantage by accumulating heterogeneous resources (Barney,1991; Peteraf,1993) in an organization through complementarity and co-specialization (Powell and Dent-Micallef, 1997). Whereas complementarity is defined as being when the value of one resource is enhanced by the presence of other resources (Powell and Dent-Micallef, 1997), co-specialization is defined as being when one resource has little or no value without another (Clemons and Row, 1991).

Although resources represent the raw materials in the quest of attaining competitive gains, they are insufficient without the underlying ability to utilize and mobilize them in order to harness their potential. Therefore, the notion of resource was subsequently further split to encompass the processes of resource-picking and capability-building, two distinct facets central to the RBV (Amit & Schoemaker, 1993).

Capabilities are defined as a "firm's capacity to deploy resources, usually in combination, using organizational processes, to effect a desired end" (Ambrosini et al. 2009, p. 35). According to the definitions of Amit and Schoemaker (1993) resources are regarded as tradable and non-specific firm assets, while capabilities as non-tradable firm-specific abilities to integrate, deploy, and utilize other resources within the firm. In this sense, resources represent the input of the production process while a capability is the capacity to deploy these resources with the aim of improving productivity.

Moreover, based on the idea that firms must be both stable enough to continue to deliver value in their own distinctive way, and agile and adaptive enough to restructure their value proposition when circumstances demand it, there is a well-documented distinction between operational and dynamic capabilities.

In the resource based view (RBV), operational capabilities have been identified as an important source for the generation of sustainable competitive advantages (Barney, 1991). Operational capabilities are those that allow a firm to make a living in the present. Operational capabilities have been conceptualized and measured in empirical research as a higher-order construct, consisting of the dimensions of marketing and technological capability (Agarwal, Selen, 2009; Spanos, Lioukas, 2001; Wilden, Gudergan, 2015). A marketing capability refers to the capacity of a firm to link with and serve particular customer groups (Danneels, 2008) while technological capabilities reflect the organizational capacity to employ technologies to convert inputs into outputs (Afuah, 2002).

Nevertheless, conditions of high environmental uncertainty, market volatility, and frequent change, have raised questions regarding the rate to which operational capabilities erode and cease to provide competitive gains (Drnevich, Kriauciunas, 2011).Thus, it is suggested that in such circumstances the focus should be shifted to strengthening capacities of change and re-adjustment of operational capabilities. The dynamic capabilities view has been used to address this issue (Teece et al., 1997). The dynamic capabilities view repositions the focus on the renewal of existing organizational capabilities as a means of competitive survival for the firm (Winter, 2003). Therefore, the main differentiation between operational and dynamic capabilities is that the former allow firms to make a living in the present, while the latter enable their modification in response to the shifting external environment (Winter, 2003).

Researchers have identified distinct and measurable dimensions of dynamic capabilities (Teece, 2007; Pavlou & El Sawy, 2010; Mikalef et al., 2016; Mikalef &Pateli, 2016). These dimensions include sensing, learning, coordinating, integrating and reconfiguring (Mikalef et al., 2016). A sensing capability concerns the capacity of a firm to spot, interpret and make sense of opportunities and threats in the business environment (Teece, 2007). A learning capability is defined as the capacity to acquire, assimilate, transform and exploit new knowledge that enables informed decision making (Zahra &George, 2002). A coordinating capability is defined as the ability to orchestrate and deploy tasks and resources and synchronize activities with involved stakeholders (Pavlou &El Sawy, 2011). An integrating capability includes the capacity to evaluate external resources and competences and embed and exploit them in a new or revamped ways (Woldesenbet et al., 2012). Finally, a reconfiguring capability is defined as the ability of a firm to effectuate strategic moves and demonstrate agility when there is a need to change existing ways of operation (Lin &Wu, 2014).

Teece (2007) argues that dynamic capabilities can be decomposed into the sensing, seizing and transforming capabilities. Sensing capabilities are “analytical systems to learn and to sense, filter, shape and calibrate opportunities” (Teece 2007, p. 1326). Identified opportunities and threats must be seized upon by building consensus among stakeholders, making effective decisions, and investing organizational resources (Teece 2007). In order to initiate organizational change, consensus building is critical to overcoming organizational inertia (Teece 2007) and is a precursor of successful strategic action (Kor and Mesko 2013). Once shared understanding is built, the organization must make strategic decisions about how to invest its resources, in other words to develop an action plan for adapting the organization's business model. Another critical element of dynamic capabilities involves the execution of organizational decisions and plans through redesigning the business model, realigning assets and revamping routines (Teece 2007). Transforming capabilities imply that the organization has the ability to direct and organize business processes in a manner that allows change to be performed effectively and in a timely manner (Helfat and Peteraf 2014; Hodgkinson and Healey 2011).

2.5. Big Data Analytics Capabilities

Extending the resource based theory perspective, the notion of BI&A capabilities is employed as an intermediary link between BI&A dimensions and organizational performance (Ramakrishnan et al. 2015; Seddon et al. 2017). A big data analytics capability is broadly defined as the ability of a firm to capture and analyze data towards the generation of insights by effectively orchestrating and deploying its data, technology, and talent (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Kiron, Prentice, & Ferguson, 2014).

Three key building blocks of BDAC are identified: organizational (i.e., BDA management), physical (i.e., IT infrastructure), and human (e.g., analytics skill or knowledge). Davenport et al. (2012) suggest that the focus should be on: big data management capability across core business and operations functions, data scientists in terms of human resource capability and advanced IT infrastructure capability. McAfee and Brynjolfsson (2012) identify the most significant dimensions of BDAC as being talent management, IT infrastructure, and decision-making capability across different functions. Similarly, Barton and Court (2012) highlight the following three dimensions of capability: big data management ability to predict and optimize models, IT infrastructure to manage multiple data sources and the expertise of front line employees in understanding the tools. Also, Kiron et al. (2014), when considering the key dimensions of BDAC, focus on management culture, data management infrastructure, and skills. Wixom et al. (2013) recognize BDA capabilities in terms of strategy, data and people to conceptualize BDAC dimensions. According to Phillips-Wren et al. (2015, p. 450), "Big data adds new dimensions to analytics. It offers enhanced opportunities for insight but also requires new human and technical resources due to its unique characteristics".

In their study, Akter, Wamba et al. (2016) propose a BDAC model which consists of three primary dimensions (management, technology and talent capability) and eleven sub dimensions (planning, investment, coordination, control, connectivity, compatibility, modularity, technical knowledge, technology management knowledge, business knowledge and relational knowledge).

BDA management capability (BDAMAC)

BDAMAC is an important aspect of BDAC ensuring that solid business decisions are made applying proper management framework. BDA management capability was found to include BDA planning, investment, coordination, and control. The BDAMAC starts with the proper BDA planning process which identifies business opportunities and determines how the big data-based models can improve firm performance (Barton and Court, 2012). Similarly, BDA investment decisions are critical aspects of BDAMAC as they reflect cost–benefit analyses. According to Ramaswamy (2013), “we found that companies with huge investments in Big Data are generating excess returns and gaining competitive advantages, putting companies without significant investments in Big Data at risk”. In addition, BDA coordination receives increased attention in the big data environment, representing a form of routine capability that structures the cross-functional synchronization of analytics activities across the firm (Kiron et al., 2014). Finally, BDA controlling functions are performed by ensuring proper commitment and utilization of resources, including budgets and human resources.

BDA technology capability (BDATEC)

BDATEC refers to the flexibility of the BDA platform in relation to enabling data scientists to quickly develop, deploy, and support a firm’s resources. Three core themes underpin perceptions of BDATEC: connectivity, compatibility and modularity. It is important to tackle volatile business conditions and align resources with long-term and short-term business strategies. Thus, the flexibility of a firm’s BDAC depends on two components: the first component is connectivity among different business units in sourcing and analyzing a variety of data from different functions. The second component, compatibility, enables continuous flows of information for real time decisions. It also helps clean-up operations to synchronize and merge overlapping data and to fix missing information. Modularity embodies flexible platform development which allows the addition, modification or removal of features to, or from, the model as needed. It helps in tapping business opportunities and improving firm performance.

BDA talent capability (BDATLC)

BDATLC refers to the ability of an analytics professional to perform assigned tasks in the big data environment. This ‘know-how’ and other types of knowledge are referred to as capabilities in this context, and can create or sustain competitive advantage (Constantiou and Kallinikos, 2014). It is proposed that analysts should be competent in four distinct but equally important skill sets: technical knowledge, technology management knowledge, business knowledge and relational knowledge. Firstly, technical knowledge refers to knowledge about technical elements, including operational systems, statistics, programming languages, and database management systems. Secondly, technology management knowledge refers to the big data resource management knowledge that is necessary to support business goals. Thirdly, business knowledge refers to the understanding of various business functions and the business environment. Finally, relational knowledge refers to the ability of analytics professionals to communicate and work with people from other business functions. Data scientists need close relationships with the rest of the business. Overall, balanced proficiency needs to be developed through ongoing training and coaching in managing the project, the infrastructure and knowledge (Barton and Court, 2012).

3. Big Data Application Fields

3.1. BDA and Innovation

Innovation is defined as "the design, invention, development and/or implementation of new or altered products, services, processes, systems, organizational structure or business model for the purpose of creating new value for customers and financial returns for the firm" (Joshi et al. 2010).

3.1.1. Models of Analytics in Innovation

George & Lin (2017) classify four different models of analytics in innovation:

Analytics as innovation: In this case, analytics is seen as a way to innovate, and can be seen in three different types of experiments. First, organizations that are trying for the first time to adopt analytics solutions into their main business process and decision-making; second, organizations that are already using certain analytics systems but are going to use a new analytics functional module for the first time; and third, organizations applying an analytics solution to a new area for the first time. According to the authors, it is likely that a majority of firms would fall within this category because analytics is still an emerging technological capability.

Innovation on analytics: In this model, organizations push for technological advances (innovation) in analytics, algorithms, products and implementation methodologies which is often seen in technology companies that are producing analytics products or in R&D organizations as a source for developing novel ideas on analytics. Organizations that perform innovation on analytics tend to have the requisite technological capability and human capital to make advances for the field.

Analytics on innovation: These organizations perform analytics on innovation-related tasks. They do this to collect data and results from innovation generation processes and innovation implementation, to do analysis, visualization and to produce deeper analytical insight. Analytics on innovation can help organizations build a stronger innovation mechanism, and can even help identify innovation diffusion within and across organizations, which will provide decision makers with support for collaborative work. Analytics on innovation can be applied to different innovation processes and tasks, such as new product development, business model innovation, business process optimization, and management innovation but the clear focus is on analytics as integral to the innovation process and its use as a testbed for novel ideas.

Innovation through analytics: The innovation process is powered by analytics, and integrated into every step of the innovation processes to develop new products or services. Among the four types, innovation through analytics is challenging for organizations as it requires analytics to be seamlessly integrated into the innovation process.

3.1.2. BDA and Absorptive Capacity

In their study, Al-Jaafreh & Fayoumi (2017) theorize and empirically examine how BDA capabilities are related to innovation by adopting an absorptive capacity perspective.

ACAP is conceptualized as the firm's ability to acquire, assimilate, transform and apply knowledge to produce a dynamic organizational capacity (Lane and Lubatkin 1998; Zahra and Geroge 2002). There are two subsets of ACAP: potential and realized absorptive capacity (Zahra and Geroge 2002). Potential absorptive capacity involves knowledge acquisition (the identification and attainment of external knowledge) and knowledge assimilation (the analysis and interpretation of external knowledge). Realized absorptive capacity involves knowledge transformation (the combination of existing knowledge with newly assimilated knowledge) and knowledge exploitation (the application of knowledge) (Zahra and Geroge 2002).

BDA is used to analyze and acquire knowledge from big data (Sun et al. 2015). According to Villars et al. (2011), big data technologies help organizations to extract value from large volumes of a wide variety of data by enabling them to capture, store, and analyze it effectively to better understand their business and customers, as well as the environment they operate in (Chen et al. 2012). Sophisticated analytical tools help organizations to exploit existing knowledge to create new knowledge, which supports knowledge transformation and exploitation capability. Thus, according to Al-Jaafreh & Fayoumi (2017), big data analytics enable firms’ absorptive capacity.

ACAP is inherent with a firm's knowledge capabilities by which it acquires, assimilates, transforms and exploits knowledge resources to produce dynamic capabilities such as innovativeness (Zahra and Geroge 2002). Daghfous (2004) pointed out that the ACAP of a firm is beneficial to organizational learning and R&D activities.

Growth of interest in both learning in organization and knowledge management occurred at very similar time which indicated the interrelatedness and interconnectedness of both issues (Hislop, 2005). Since learning cannot occur without an active pursuit and management of knowledge, the establishment of a knowledge management initiative is essential to the eventual movement to a learning culture. Knowledge management serves as a manager's framework for improving the organization's learning potential.

Organizational learning capabilities involve four dimensions namely managerial commitment, systems perspective, openness and experimentation, and knowledge transfer and integration. More specifically, managerial commitment indicates the creation of culture encouraging organizational learning recognizing its role in obtaining long-term results, systems perspective denotes viewing the organization as an integrative whole based on the coordination, collaboration, knowledge sharing and common understanding, openness and experimentation suggests the welcoming of new ideas, creativity and the promotion of enterprising culture, taking controlled risks and learning from mistakes, and finally knowledge transfer and integration refers to the elimination of internal barriers and leverage the interactions between different departments as well as individuals in terms of the transfer of best practices (Jerez-Gomez et al 2005).

Several studies in the literature argue that organizational learning capability is positively related to innovation (Calantone et al 2002; Hurley and Hult, 1998). Most studies consider that learning injects new ideas and strengthens the creativity and the ability to discover new opportunities, so it supports the presence of innovation (F.J. Lloréns Montes et al, 2005: 1160). Organizational learning capability improves innovation performance through strengthening the interactions among organizational members and departments and exchange between members and artifacts such as processes and values (Alegre and Chiva, 2008). Indeed innovative outcome is achieved through clear, fast and focused communication of knowledge across internal boundaries (Goh, 2003; Baker and Sinkula, 1999) as well as its absorption from external environment (Cohen and Levinthal ,1989). For instance, as the exchange of ideas and collaborative action increases among employees the hierarchical organizational structure is shifted towards a participative decision making which increases commitment to innovate by decreasing resistance to change and allowing the risk-sharing between all related parties (Mat and Razak, 2011). Organizational learning capability encourages the establishment of a learning culture which in turn dedicates all of its members to translate knowledge and learning into innovative outputs (Hung et al, 2010).

As suggested by Bustinza et al., (2012) dynamic capabilities are behavior patterns with which the firm systematically adjusts its operational routines so to increase its effectiveness." Since organizational learning capability is defined as the "capability of an organization to process knowledge -in other words, to create, acquire, transfer and integrate knowledge and to modify its behavior to reflect the new cognitive situation with a view to improving its performance" (Jerez-Gomez et al 2005 p. 716), it can be evaluated as part of firm's dynamic capabilities.

Theoretically, the extant literature suggests that dynamic capabilities cannot only adapt to but also shape the environment change (Eisenhardt & Martin, 2000; Teece, 2007). As innovations have been widely considered as key engines for firms to adapt to and shape the environment in which these firms operate, it is proposed that innovations serve as a mediating mechanism between dynamic capabilities and firm performance.

3.1.3. Big Data Innovation Model

In their paper Constantinides & Lorenzo (2015) briefly discuss the evolution of the innovation process from the closed to the open innovation model and on the basis of recent technology developments, business practices and market trends propose the emerging innovation model build on customer co-creation and on effective use of a fast growing customer and market data volume. According to the authors (Constantinides & Lorenzo, 2015), in the Big Data Innovation Model the customer co-creates in new product development process by participating in the innovation process directly and deliberately or indirectly and unintentional. Customer data critical for co-creation is produced by traditional and online interactions, transactions and social media activity but recently two new sources of customer data are expected to be added in the equation: the Internet of Things and the Neuromarketing.

The closed innovation model describes the new product development as a linear, internally oriented process that begins with the idea generation and ends with the product commercialization (Kotler and Keller, 2006) (p. 640). It requires the presence of clear organizational structures and pays very limited attention to customer involvement in most stages. Secrecy is one of the foundations of this type of innovation and main disadvantages of the closed innovation model are the high innovation costs, long time-to-market and high failure rates of new products (Kotler and Keller, 2006).

The open innovation paradigm advocating innovation in networks emerged as key research topic providing answers to the 21st century innovation challenges (Kambil, Frissen and Sundaram, 1999; Thomke and von Hippel, 2002; Chesbrough, 2003; von Hippel, 2005; Chesbrough and Crowther, 2006). The most obvious places to look for innovation partner networks is according to most authors the business value chain and the lead users. Engaging value chain partners or lead users helps realizing substantial cost and time savings and reduce new product failure rates.

Customer engagement in social media activities produces large volumes of data and part of this data is directly relevant for the innovation process. Such content can be obtained by marketers in two different ways.

One way is through monitoring and processing data from the social media space by "listening" to online customer voice. Forums, blogs, review sites, social networking sites and online communities are some of the applications where innovation-related social customer voice can be found. Collecting and mining such content provides businesses with valuable information about market needs and trends. Properly analyzed social intelligence data helps businesses improve products and services, respond to complaints and prevent problems (Constantinides and Fountain, 2007). The social data can be useful at all stages of the innovation process: idea generation, idea screening, concept development, product testing and the early stages of the commercialization process.

Another way is through engaging innovative customers by attracting them in social online innovation platforms. This approach targets a new generation of empowered and smart consumers increasingly demanding a greater role in the development of products they buy (Piller, Moeslein and Stotko, 2004). Empowered consumers are often willing to actively participate in the innovation process (Nambisan, 2002; Ogawa and Piller, 2006; Lee, Constantinides, Lorenzo and Gómez-Borja 2008; Olson and Trimi, 2012) in social online interactive environments known as Virtual Customer Environments (Nambisan and Baron, 2009).

The Internet of Things (IoT), is a fast growing network of internet-connected embedded devices like sensors, actuators, machines and wearables allowing ubiquitous connectivity of machines, systems, factories, vehicles, homes, cities and people (Gubbi, Buyya, Marusic and Palaniswami, 2013; Carretero and García, 2014 ; Miorandi, Sicari, De Pellegrini, and Chlamta, 2012). Part of the vast volumes of data created in the IoT domain can be used by marketers in different ways and specifically as input in innovation projects. This is expected to take place along the Front End of the innovation process by creating "connected marketplaces" where "creative data manipulators" collecting and analyzing data for example from smart homes and their inhabitants will provide innovative insights and customer needs by detecting behavioral patterns (Kortuem and Kaswar, 2010). Such information can be also used for compiling exact user profiles, which subsequently will be used to design products and services specifically targeting individual or segment needs (Guo et al., 2012). In the Back End of the innovation process IoT data will be collected from connected products in use by beta testers or early adopters before the products reach wide scale distribution. Analysis will identify problems or will detect usage patterns indicating discrepancies between the actual use of the product and the intended use leading to design changes and improvements of the final product.

Finally, applying neuroscience technologies and processes for marketing purposes, widely known as neuromarketing, is an approach that allows marketers to better understand human behaviour in new ways (Lee, Broderick, & Chamberlain, 2006) and understand the mechanisms of decision making in the subconscious of the human brain (Ariely & Berns, 2010).

3.1.4. BDA and Product Innovation

In their research, Duan & Cao (2015) investigate the mechanism through which business analytics contributes to a firm's product innovation. Kim et al (2013) review the relevant literature and adopt Amabile's (1983) two dimensional perspective on product creativity that is composed of novelty and meaningfulness. They define the new product novelty as the degree of the originality and unique differences of the new product, and meaningfulness as the degree to which a new product provides appropriate and useful aspects to target customers (Kim et al., 2013).

Duan & Cao (2015) suggest that business analytics directly improves environmental scanning which in turn helps to enhance a company's innovation in terms of new product novelty and meaningfulness.

Environmental scanning is a basic process of any organization to acquire data from the external environment to be used in problem definition and decision making (Thayer, 1968). The primary purpose of environmental scanning is to provide a comprehensive view or understanding of the current and future condition of the different environmental constituents and use this view as a foundation for guiding product/service development (Maier et al., 1997). Environmental scanning refers to a firms' activities to gather information about its environment (Miller and Friesen, 1982). Consequently, according to Duan & Cao (2015), information processing and use help to generate insights into a firm's changing environment, especially the needs for innovation, perhaps due to changing customers' desires, buying patterns or new development of competitors.

Keller & Holland (1975) and Tushman (1977) argue that a primary limitation on a firm's innovativeness is its ability to recognize the needs and demands of its external environment through environmental scanning. Miller and Friesen (1982) considered environmental scanning as one of the important variables in their innovation study in conservative and entrepreneurial firms. Previous innovation studies (e.g. Miller and Friesen, 1982) have confirmed the contributions of environmental scanning to new product innovation and competitive advantages.

Another key finding of their research (Duan & Cao, 2015) is that the effect of business analytics' contribution would be increased through the mediation role of data-driven culture in the organization based on the proposition that information technology can be an important determinant of organizational strategy, culture, processes, and/or structure (Hsiao and Ormerod, 1998, Jelinek, 1977, Lee and Grover, 1999, Perrow, 1967, Woodward, 1958, Woodward, 1965, Yetton et al., 1994). Prior studies have emphasized that in order to reap the benefits of using business analytics, a company needs to develop a data-driven culture where managerial decisions rely more on data-based insights (Davenport et al., 2001, Kiron et al., 2012, Kiron and Shockley, 2011, Lavalle et al., 2011). According to Kiron et al. (2012), a data-driven culture refers to "a pattern of behaviors and practices by a group of people who share a belief that having, understanding and using certain kinds of data and information plays a critical role in the success of their organization" (p. 12). This means essentially that explicit organizational strategies, policies and rules are to be developed to guide business analytics activities, and well-defined organizational structure and business processes are in place to enable business analytics activities to be well coordinated (Kiron et al., 2012, Kiron and Shockley, 2011, Lavalle et al., 2011).

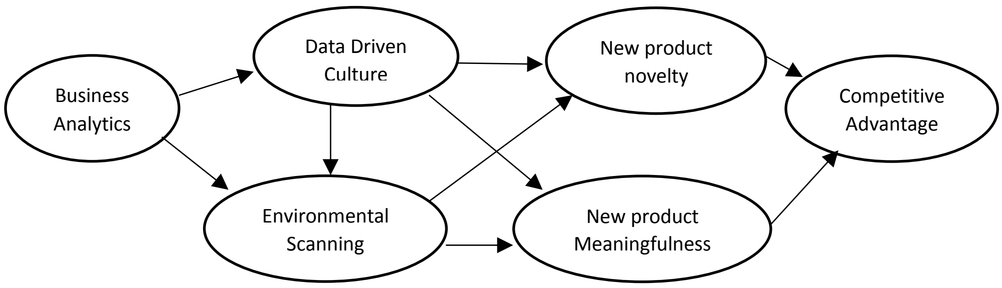

Fig. 1: BDA and Product Innovation (Duan &Cao, 2015)

Duan & Cao (2015) also assert that data-driven culture positively impacts on new product novelty and product meaningfulness. Organizational culture is the pattern of shared values, norms, and practices that distinguish one organization from another (Higgins and McAllaster, 2002). The relationship of organization culture and innovation has been subject to extensive research over the last decades (Büschgens et al., 2013) and its role in innovation has been well investigated and discussed by researchers (e.g. Denham and Kaberon, 2012, Kenny and Reedy, 2006, Wyld and Maurin, 2009). Lau and Ngo (2004) argue that a certain type of culture is needed to effect changes in organizations so that innovative and entrepreneurial behaviors could be encouraged. In the context of big data and business analytics, authors (Duan & Cao, 2015) focus on data driven culture.

3.1.5. BDA and Service Innovation

The ever increasing abundance of data, coupled with advances in big data analytics (BDA) offer new possibilities for service innovation (Barrett et al., 2015; Yoo et al., 2012). BDA provides powerful methods and tools for gathering, processing, and analyzing large amounts of trace data, enabling organizations to generate valuable insights by compiling their customers' "digital footprints into a comprehensive picture of an individual's daily life" (Zhang et al., 2011). These insights have the potential to create competitive advantage (Constantiou, Kallinikos 2015; George et al., 2014; Newell, Marabelli, 2015), and BDA is expected to support customer-oriented service innovation in a number of ways (Orlikowski, Scott, 2015; Yoo et al., 2012).

The view of service innovation has shifted from a focus on firms' output to a focus on new ways of creating customer value through service processes, so the shift has been from a goods-dominant (G-D) logic to a service-dominant (S-D) logic. Here, the value of an innovation is not delivered to the customer as a product but can offer a promise of value creation—that is, value propositions. Customers approve these propositions by engaging with the firm's service process, thereby co creating value with the firm (Skålén et al., 2015). Service innovation, then, is the creation of value propositions, which are generated when firms deliver resources to improve the customer's own value creation. Organizations therefore renew their service-delivery processes to provide new value propositions to their customers (Skålén et al., 2015), and this renewal becomes the essential source of service innovation.

In their study, Lehrer, Wieneke et al. (2018) present a theoretical model of BDA-enabled service innovation that extends prior work on IT-enabled service innovation (Barrett, 2015; Lusch, Nambisan, 2015; Orlikowski, Scott, 2015) by explaining how service automation and human-material service practices yield service individualization, grounded in the material features of BDA technologies: sourcing, storage, event recognition and prediction, behavior recognition and prediction, rule-based actions, and visualization.

Their model highlights how both material agency and human agency play roles in shaping organizational service processes and in creating value propositions for customers. In the case of service automation, the focus is on material agency (Leonardi, 2011). In contrast, in human-machine service practices, human and material agencies interpenetrate in what Pickering (1995) referred to as the "mangle" of practice (Pickering, 1995), and human agency is enacted in response to the technology's material agency (Leonardi, 2011; Volkoff et al., 2007). In the case of service automation, BDA technologies provide both necessary and sufficient conditions for service innovation, as the technology acts without the intervention of human actors. In the case of human-material service practices, BDA technologies provide only necessary conditions, as the observable practice results from the interpenetration of human and material agencies in practice.

To implement service automation, organizations use algorithmic solutions that are based on the material features of BDA in terms of trace data sourcing and storage, event recognition and prediction, behavior recognition and prediction, and rule-based actions. Two types of service automation emerged as salient from analysis (Lehrer, Wieneke et al., 2018): automated trigger-based service action and automated preference-sensitive service action. In the first case, the system independently carries out actions (material agency) when triggered by an event thereby, providing service at the right time. In the second case, the system automatically adjusts user interfaces, for instance, by providing tailored content (material agency) when a certain user behavior on an online channel or a customer's current location are detected, thereby, providing service in the right way.

BDA technologies afford human service actors new ways of interacting with customers, leading to human-material customer-sensitive service practices that are consistent with new action goals related to service individualization, such as proactively approaching and interacting with a customer. Two types of human-material service practices emerged as salient from analysis (Lehrer, Wieneke et al., 2018): trigger-based customer service interaction and preference-sensitive customer service interaction. In the first case, the system provides service actors with trigger information (material agency), such as a customer's business-related lifetime event, after which the service actor proactively approaches and interacts with the customer (human agency). In the second case, the system uses customer profiles to make recommendations for actions (material agency), allowing the service actor to adjust interaction with the customer (human agency).

Thus, according to Lehrer, Wieneke et al. (2018), BDA facilitates proactive service provision that is based on insights into the customer and the customer's context. Service provision has typically been reactive in nature, requiring customers to approach the firm with a service request. However, digitized objects enable firms to gather and analyze data generated by the customer outside the business relationship in the customer's private sphere. Using such data to initiate timely interactions enables firms to extend their service value chains and support their customers in various life situations precisely when they need it. Being aware of customers' problems in everyday life facilitates the firm's development of new value-added service and improves the customer's experience and perception of the value the firm offers.

In addition, BDA increases the speed of service provision—even real-time service provision. For this purpose, service based on BDA is often provided through automated systems that facilitate immediate action (Lehrer, Wieneke et al., 2018). This approach to real-time service provision is in line with the basic tenets of BDA analytics in terms of the velocity with which new data are generated and analyzed (McAfee, Brynjolfsson, 2012), and it adds another nuance to how organizations create new value propositions under an S-D logic (Barrett et al., 2015; Lusch, Nambisan, 2015).

Finally, Lehrer, Wieneke et al. (2018) assert that enabled by insights gained into the customer both inside and outside the business relationship, service can be highly individualized and tailored to customers' needs. Instead of mass customization, BDA enables firms to tailor service cost-effectively to a "segment of one" by using knowledge gained from analyzing the customer's behavioral patterns.

3.1.6. BDA and Business Process Improvement

Firm's process innovation capability is defined as a firm's ability, relative to its competitors, to apply the collective knowledge, skills, and resources to innovation activities relating to new processes, in order to create added value for the firm (Hogan, Soutar et al., 2011). Process innovation is important since it is closely associated with product innovation (Adner, Levinthal, 2001). In their empirical investigation, Fritsch and Meschede (2001) show that process innovation has a positive effect on product innovation. More specifically, by fostering process innovation, a firm will be able to improve its product quality or even to produce entirely new products. Two main types of process innovation capabilities are identified, incremental and radical (Ettlie, Bridges et al., 1984). An incremental process innovation capability is defined as an organization's ability to reinforce and extend its existing expertise in processes, by significantly enhancing or upgrading them (Gallouj & Savona, 2009). On the other hand, a radical process innovation capability is focused around the ability of the firm to make current/existing processes obsolete through the introduction of novel ones (Subramaniam & Youndt, 2005).

In their study, Torres, Sidorova & Jones (2018) adopting view offered by Teece (2007) regarding dynamic capabilities, viewed BI&A as the sensing and seizing components of them that contribute to firm performance by enabling business process change.

Sensing opportunities and threats requires the acquisition and interpretation of information about both the internal operation of the firm and its environmental context (Schreyögg and

Kliesch-Eberl, 2007; Teece, 2007). BI&A can provide this type of capability (Sidorova and Torres, 2014).

The ability to gather and analyze data implied by the BI&A sensing capability requires specialized IT infrastructure, often consisting of data storage, management and analysis tools (Elbashir et al., 2008). The sophistication of BI&A infrastructure is a key factor in the successful use of BI&A solutions (Elbashir et al., 2013). The quality of BI&A technical infrastructure encompasses both data quality and system quality. Data quality is essential in the context of BI&A because it directly influences the validity of the insights derived from that data (Yeoh and Koronios, 2010).Thus, according to Torres, Sidorova & Jones (2018), BI&A infrastructure is positively related to sensing capability.

It is also stated that personnel expertise affects positively sensing capability (Torres, Sidorova & Jones, 2018). A clear understanding of both the relevant technology and the business domain have been identified as critical to the success of BI&A systems (Clark et al., 2007; Clark and Jones, 2008; Najjar and Kettinger, 2013; Seddon et al., 2017). Highly capable BI&A personnel are expected to produce information that is more accurate, useful, and insightful than personnel with lesser skills.

BI&A management capability is the ability of the organization to manage and ensure the use of BI&A resources. Management support help ensure high quality of both the BI&A system and its underlying data (Wixom and Watson, 2001), and thus influence the quality of the BI&A technical infrastructure.

BI&A management capabilities are also critical to the attraction, selection, development, and retention of necessary expertise among producers and consumers of BI&A output (Kiron et al., 2011) and to the creation of analytical culture that make decision makers feel comfortable with the use of analytical models. Based on the abovementioned, it is advocated that management capability is positively associated with BI&A technical infrastructure quality and personnel expertise (Torres, Sidorova & Jones, 2018).

An organization can fully optimize the BI&A benefits if it has the management ability to leverage BI&A resources (Gessner and Volonino, 2005). The ability to sense opportunities and threats relies on the use of BI&A resources to develop organizational insight. Thus, BI&A management capability is expected to have a positive effect on sensing capability (Torres, Sidorova & Jones, 2018).

Seizing involves the integration and interpretation of information in order to arrive at a decision to act as well as planning the commitment of resources to support that action (Teece, 2007).

This is consistent with the view that effective BI&A should result in an impetus for organizational change (Sidorova and Torres, 2014).

Superior BI&A sensing capabilities help create a more comprehensive picture of organizational threats and opportunities, and they help reduce uncertainty in decision making (Chakravarty et al., 2013; Teece, 2007) developing an effective plan of action that is supported by stakeholders. Organizations with superior BI&A sensing capabilities are expected to identify a greater number of opportunities than their counterparts without such capabilities. As a result, such organizations are expected to practice their seizing capabilities more frequently, which is necessary for the successful maintenance and improvement of these capabilities (Winter, 2003).

This is consistent with the dual model of process dynamization (Schreyögg and Kliesch-Eberl, 2007). In contrast to the conceptualization of dynamic capabilities as merely the ability to reconfigure organizational routines and processes in response to a request for change (Zahra et al., 2006), the dual process approach to capability dynamization puts an emphasis on capability monitoring and the ability to recognize the need for change and the direction for such change. The capability dynamization view of BI&A distinguishes between the operational level (capability practices) and the observational level (capability monitoring). At the operational level, capabilities are enacted through the execution of business processes, which may range from standardized to highly knowledge intensive (Dalmaris et al. 2007; Trkman 2010). Capability monitoring is implemented via BI&A. Capability practices generate data, which, when captured, are used as an input into capability monitoring via BI&A. Analysis of changes in the external environment is also a key component of capability monitoring. Therefore, data from external sources constitute another input into BI&A. Consistent with the dual process model of capability dynamization (Schreyögg and Kliesch-Eberl, 2007), the BI&A capability dynamization model defines requests for change in existing business processes and structures as the key output of BI&A. Implementation of requests for change results a modified capability, such as a new version of a business process.

Transforming involves the creation, renewal, or reconfiguration of the firm's ordinary capabilities in response to organizational decisions to act (Teece, 2007). Business process change capability is conceptualized as the transformational component of organizational dynamic capabilities. BPC capability is defined as is the firm's ability to effectively alter its business processes to exploit identified opportunities and avoid threats. BPC capabilities are necessary to translate the action plan developed through BI&A seizing capabilities into improved ordinary capabilities, and ultimately, improved organizational outcomes.

Business process change depends on BI&A seizing capability. Execution of an action plan usually requires the support of various stakeholders (Parmar et al., 2010; Teece, 2007). Superior

BI&A seizing capability is expected to result in a shared understanding of organizational opportunities and threats as well as the agreement on a chosen plan of action among key stakeholders. This allows an organization to overcome resistance and inertia, which are common obstacles of business process change (Hammer, 2015).

Finally, based on the abovementioned, Torres, Sidorova & Jones (2018) assert that BI&A enabled dynamic capabilities can enhance firm performance by promoting incremental improvements through efficiency and effectiveness on business processes. Improving the efficiency of organizational processes reduces the costs associated with the operation of the firm, thereby improving its bottom line (Ramirez et al., 2010) and effectiveness ensures that products and services produced are commensurate with the needs of internal and external customers.

3.2. Marketing Perspective of Big Data

3.2.1. Big data Applications in Marketing

Sheng et al. (2017) identify in the literature several applications of big data in the field of marketing that are analyzed as follows:

<u>Consumer behavior</u>

Consumer behavior reflects the decision making process of customers in selecting, purchasing, utilizing the product or service. It is a complicated process and affected by diversified factors. Previous big data researches try to understand consumer behavior using big data (e.g. mobile, social media data) or considering online social network influence.

User behavior

Under this topic, there are three aspects to view this issue. The first one links to mobile analytics, which examines the mobile Internet usage behavior and user engagement. It has been discovered that geographical mobility of users and social network have positive influences on mobile Internet usage behavior while multimedia content generation have negative influence (Ghose and Han, 2011). Besides, ranking effects (Ghoseet al., 2013) and rewarding (Claussen et al., 2013) promote user engagement and mobile app success, which can increase corresponding mobile website visit (Xu et al., 2014). Second, purchase behavior is affected by various factors, such as online social media brand community (Goh et al., 2013) and interactive social influences (Zhang et al., 2014). Thus concurrent learning of users' behavior is beneficial to real-time, intent-based optimal interventions, which increases purchase likelihood (Ding et al., 2015). In addition, learning behavior is also investigated in prior studies using video stream, blogs and other data to detect the interaction and learning pattern.

Online community

The increasing interaction via the Internet brings out online community, which is a virtual community where members acquire information and communicate with each other through social network platform. Current studies focus on detecting online community as well as identifying characteristic within the community. Several papers propose methods to detect groups in virtual communities (Chau and Xu, 2007; Wang et al., 2013b), discover information (Garg et al., 2011), and identify community (Ludwig et al.,2014). Furthermore, within the online community, leadership and identification emerge, especially the linguistic style match, which shape the community dynamics (Johnson et al., 2015) and drive the network growth (Lu et al., 2013).

Social network effect

Consumer behavior is also influenced by social network, where the pattern and dynamics, and influencing entities may have great impact. Through analyzing social network, adoption probability can be predicted (Fang et al., 2013). Besides, social media can enrich network information, which has positive effect on work productivity and job security (Wu, 2013), brand and retailer performance as well as consumer-retailer loyalty (Rapp et al., 2013). In particular, online user-generated content has positive relation with their social ties and its network effects can boost advertising and revenue growth (Shriver et al., 2013).

Consumer sentiment

Consumer sentiment reflects consumer's feelings, perception, and evaluation of product or service. In e-commerce, online review and rating systems have been designed to detect consumer's opinion and sentiment towards specific commodity (Dellarocas et al., 2007). Besides, sentiment analysis is a hot topic with advancement in analytics techniques and application. One point to note here is that studies on big data from the consumer perspective is not limited to marketing purposes. Looking into consumer opinions can also shed light on operation and production improvement.

Online review

Online review is a form of e-WOM communication and analyzing the user-generated contents can potentially predict future sales and assist marketing strategy (Archak et al., 2011; Moon et al., 2014; Lee and Bradlow, 2011). As it has significant impact on consumers' choices, it is important to predict and improve the helpfulness of reviews. Several studies (e.g. Baek et al., 2012; Cao et al., 2011) investigate the influencing factors of review helpfulness and try to predict helpfulness by looking into text linguistic features or reviewer engagement characteristics (Krishnamoorthy, 2015; Ngo-Ye and Sinha, 2014). Furthermore, online reviews have social influence on other consumers (Sridhar and Srinivasan, 2012), such as their perception of reviews (Cheng and Ho, 2015) and way of writing reviews (Goes et al., 2014; Ludwig et al., 2013). It can also be utilized to measure customer satisfaction with greater effectiveness and efficiency (Kang and Park, 2014). In addition, to enable deeper analysis of product reviews, several advanced text-mining approaches are explored based on language, web or topic structure, which forms part of research in this topic.

Online rating

It normally takes a form of numerical rating where consumers evaluate the products or services by giving scores. The ranking systems analyses user-generated content to assess customer's preference hence provide best-fit product and service (Ghose et al., 2012). Indeed, Moe and Trusov (2011) illustrate that online product ratings dynamics have direct and immediate effects on sales. Sun (2012) further proves a higher variance of product ratings can help with sales increase only if the average rating is low. Besides, online ratings have social influence on other user's rating behavior (Lee et al., 2015). However, Hu et al. (2012) found that firm manipulation in product rating requires further attention from the business operators.

Sentiment analysis

Sentiment analysis extracts and classifies subjective information in various data sources, which can be applied to improve business intelligence. A synonym, opinion mining, often refers to the same field of study, and we use this term to categories general studies on this topic. Overall, opinion mining provides useful information for decision-making (Alfaro et al., 2013). Especially the marketplace sentiment can advance the way of understanding consumers which is beneficial to niche market identification (Gopaldas, 2014; Jang et al., 2013; He et al., 2015) and brand positioning (Mostafa, 2013). Web comment text, social media, product reviews and other user-generated contents are commonly used in these studies. In addition, sentiment detection and classification as part of sentiment analysis also attracts research interests. Based on practical purposes, a lot of new methods are explored to detect emotions (e.g. Balahur et al., 2012; Gao et al.,2015b), spot topics (e.g.Li andWu, 2010), and improve sentiment classification accuracy (e.g. Colace et al., 2015a; Khan et al., 2014; Da Silva et al., 2014). They are broadly applied to analyze sentiment and opinions of consumers and market, so as to enhance the overall management efficiency.

Marketing strategy

Big customer data facilitates more specialized market segmentation, which advances marketing strategies such as personalized advertising, brand improvement, and recommendation. Besides, the predictive analytics can examine the real-time marketing performance and influential factors, which enables dynamic adjustment of advertisement strategy (Nichols, 2013).

Advertising and targeting

Advertising is a form of marketing strategy aiming for promoting and selling the product or service, and targeting as a type of advertising segments consumers and communicates with them based on specific behavioral, demographics, psychographics and other features. In recent research, mobile targeting and advertising has been proved to be effective for location-based services (Li and Du, 2012). By incorporating locational and geographical parameters, retailers have more power in offering discriminated prices (Fong et al., 2015) and increase sales (Luo et al., 2014). Andrews et al. (2016) illustrate that physical crowdedness has positive impacts on consumers' response to mobile ads, which is beneficial to hyper-contextual mobile advertisement. Nonetheless, social effects on advertising may vary across markets with different demographic characteristics and groups (Gopinath et al., 2013).

Brand analysis

Generally, brand analysis pins down brand position in market, brand perception by consumers, and competitors' brand performance, and so on forth. Regarding big data brand analysis, investigations are most done in a social and consumer context. For example, social media strategic capability can enhance brand innovation (Nguyen et al., 2015) and social tagging has great implications for brand performance measurement and brand equity management (Nam and Kannan, 2014). Besides, online information has an influence on consumers' perception of brands and Camiciottoli et al. (2014) find consistent brand associations in online community of international consumers. Moreover, dynamic analysis of online user-generated content can reflect consumer satisfaction with quality thus improve competitive brand positions (Tirunillai and Tellis, 2014). But, it is worth noticing that analysis of brand sentiment cannot ignore the differences across different social media venue formats (Schweidel and Moe, 2014).

Market analysis

The review indicates that there are several directions in leveraging big data in market analysis. One is market prediction by mining textual and web information from company websites (Nassirtoussi et al., 2014). It has been proven that such information is useful to predict commercial success (Thorleuchter and Van den Poel, 2012). A second area is using user-generated contents to enhance marketing efficiency. It can be applied to improve mapping of market structure (Netzer et al., 2012), detect customer-website interaction (Sch€afer and

Kummer, 2013), and identify future profitable customers more accurately (D'Haen et al., 2013; Thorleuchter et al., 2012). Especially in the era of e-commerce, via capturing detailed customer behavior information, the knowledge management strategy in marketing can help companies gain competitive advantages in business activities through establishing better interpersonal relations to customers, suppliers, business partners and employees. Digital data plays an increasing important role in B2C and B2B marketing, but there are also challenges facing companies that need to be further addressed (Leeflang et al., 2014).

Recommendation and e-WOM

In Web 2.0 era, recommendation is becoming more customized. User-generated content and their sentiment are analyzed to improve accommodating customer needs (Colace et al., 2015b; García-Cumbreras et al., 2013; Hyung et al., 2014). Personalized recommendation is achievable with technology improvement and big customer data (Rust and Huang, 2014). According to the findings in Brown et al. (2011), more advanced analysis and customization are attainable with the use of real-time and wide ranging data streams. Through routing location (Yang et al., 2008), social network (Chung et al., 2015), community (Feng et al., 2015), and personalized information (Fan et al., 2006), user preference and behavior can be detected and predicted, which promotes personalization in marketing entering a higher level. Another powerful tool in recommendation is word-of-mouth, which is an effective form of advertising. In a digital world, online communications and interactions are more frequent. Such electronic word-of-mouth (eWOM) has expanded impact through Internet on consumer perception and purchase decisions. Many studies have addressed the e-WOM and its impact on sales and consumer behavior. From the marketing lens, customer is the priority and understanding their behavior is the primary concern for marketing researchers. However, information overload may also lead to adverse effects to marketing and firm performance, which has not been well considered in current literature. Besides, the marketing practice should be integrated into higher strategic framework to guide more efficient segmenting and pricing, and this leave research spaces for revenue management and strategic management. In addition, it is understudied in prior studies that what roles the firms play in the digital marketing campaign and their engagement in the online communication activities is an interesting area to be explored in future.

3.2.2. BDA and Value co Creation

In their study, Xie, Wu et al. (2016) connect big data with S-D logic and theorize the process of big data transformation from resources to assets.

Service dominant logic is one of the most important theories that explain value co-creation between firms and customers (Vargo, Lusch, 2008; Vargo, Lusch, 2004). S-D logic defines service as the application of specialized competences for the benefit of another actor or the self (Vargo, Lusch, 2004; Voima et al., 2013). Another contribution of S-D logic is that it challenges traditional value creation logic which implies that value is transferred from firms to customers. S-D logic clarifies that value is customer centric and co-created by both firms and customers (Bettencourt et al., 2014; Voima et al., 2013). Value co creation research defines co creation as joint actions by a customer and a service provider through direct interactions (Gronroos, 2012).

S-D logic repositions the role of firms and customers within the value co-creation context. Firms are viewed as service providers (Vargo, Lusch, 2008; Vargo, Lusch, 2004) and resource integration is considered fundamental for service provision in S-D logic (Bettencourt et al., 2014; Barrett et al., 2015; Lusch, Nambisan, 2015). Building digital platforms is an important way for the integration of resources by firms (Edelman, 2014). Customers are viewed as operant resources that is, they are capable of integrating skills and knowledge into co-creation processes (Vargo, Lusch, 2008; Vargo, Lusch, 2004). Lusch and Nambisan identify three broad roles of customers: buyer, ideator, designer and intermediary.

According to Xie, Wu et al., (2016) two types of heterogeneous digital resources emerged in their study: customer generated data and firm provided big data digital platforms. In other words, in the context of big data, generating data is the primary contribution of customers to value co creation and providing a digital platform that facilitates the collection, storage and analysis of the data is the primary contribution of firms to value co creation.

Drawing on Lusch and Nambisan, Xie, Wu et al. (2016) identify four types of big data generated from the four different customer roles.

The buyer role of customers generates transactional data. Purchasing behavior is the main source of transactional data.

The role of ideator generates communication data. Communication with firms when purchasing through interactive websites, instant message, and telephone lines produces unstructured communication data. Group communication behavior generates communication big data that is non transactional. Customers use virtual social platforms that are either provided or built by firms.

The designer role of customers generates participative big data. Participative big data refers to the data generated by customers who actively participate in product or service development using their knowledge, resources and skills.

The intermediary customer role generates transboundary big data. Transboundary big data refers to data generated by customers who share different service ecosystems and facilitate the export and import of knowledge across different ecosystem boundaries. Customers act as intermediaries because the internet significantly reduces switching costs and searching cost for customers and enables them to try different brands, products, or purchases on different online platforms. This transboundary customer behavior facilitates knowledge sharing in different ecosystems.

Authors (Xie, Wu et al., 2016) also identify four types of firm provided big data platforms:

A transactional platform is a digital service platform that supports customer purchasing and enables the collection of transactional data, the transmission of data for analysis and rapid responses back to customers.

Communication platforms are digital service platforms that support customer group communication and enable the collection and transmission of communication big data. Generally, they are built by firms who want to attract customers with different themes.

Participative platforms support firms' effect to attract customers to participate actively in product improvement and to reconfigure new services or new business decisions.

Transboundary platforms support firms in acquiring new knowledge shared by customers who build connections across diverse ecosystems. Establishing or joining a multi brand and multi industrial virtual community is an efficient approach for firms establishing a transboundary platform.

Findings (Xie, Wu et al., 2016) indicate that simply owning heterogeneous digital resources is not equivalent to possessing cooperative assets. Only when resources are used through cooperation can it be transformed into valuable assets. In this study cooperation is defined as one actor's behavior in creating value for the other actor.

Cooperative capability reflects the ability of an actor to transform the heterogeneous resources into valuable and governable assets.

Three big data related abilities applied by firms form the cooperative capability of firms to capitalize heterogeneous customer resources (Xie, Wu et al., 2016): the ability to acquire, analyze and commercialize big data. Big data acquisition refers to data collection, storage, and transmission leveraging transactional and communication platforms. Firm's ability to analyze and use big data determines whether these digital resources create economic benefits for firms.

Three big data related abilities applied by customers form their cooperative capability to capitalize heterogeneous firm resources (Xie, Wu et al., 2016): the ability to search for information, to learn new technologies and to participate in value co creation. Customer ability to search for information and the ability to learn new technologies determine whether firm provided platforms are accessed or used by customers. By searching for information customers experience various digital platforms provided by firms and acquire needed information. Through information searching and learning a portion of customers develops the ability to participate in value co creation. The greater the participating ability the more benefits the customers will be able to acquire.

Interactions between the four types of big data resources and the four types of digital platforms transform these resources into four categories of cooperative assets through the applications of customer and firm cooperative capability. Firms and customers become cooperative assets with current or future economic benefits that could be acquired or controlled by the other actor in the value creation process.

Cooperative assets provide bilateral benefits to the cooperative actors in value co creation processes (Xie, Wu et al., 2016). Both firms and customers benefit from the cooperation. Transactional cooperative assets bring transactional benefits for firms that are reflected in the enhancement of sales performance. Customer transactional benefits are reflected in the economic gains in customer transactions or activities associated with a transaction. Xie, Wu et al. (2016) identify three customer transactional benefits. First, satisfaction from business exchanges. A convenient trading platform provided by firms helps identify what customers need and allows them to enjoy fast and hassle free return services. Second, economic benefits by building a bridge between firms and new customers. This reflects the interests of customers who act as transactional intermediaries. Third indirect economic benefits from business exchanges. Customers who become corporate members can enjoy the preferential trading offered by third party corporate partners.

Communication cooperative assets have a positive impact on firms with marketing benefits such as improvements in corporate marketing activities in terms of efficiency or effectiveness. Information sharing among consumers will enhance their understanding of the brand thereby strengthening brand awareness and loyalty. Communication cooperative assets also bring customers social benefits. Social benefits reflect the emotional satisfaction or social capital that customers possess. Customers make friends through virtual communication platforms. Customers with the same problem or a common interest interact with each other by asking, answering or sharing ideas.

Participative cooperative assets mainly bring operating benefits for firms. Operating benefits reflect improvements in operational efficiency or effectiveness. They also bring customized benefits for customers. Customized benefits are realized when firms configure product in accordance with the specific recommendations or requests of customers and they are equivalent to a customized offering from the firms to these customers.

Transboundary cooperative assets bring knowledge benefits for both firms and consumers. Firms can analyze transboundary data to acquire heterogeneous knowledge shared by customers of other brands. In addition, transboundary learning helps firms identify differentiated brand appeal and capture heterogeneous marketing knowledge. This helps firms to adjust their market positioning, business strategy or product development. Meanwhile, consumers can search and become familiar with similar brands or products through the transboundary platforms to enhance their knowledge of brands or products from different firms and competitors which helps them optimize the brand selection and purchase decisions.

Study of Xie, Wu et al. (2016) offers an alternative business strategy for firms to address the fierce competition in the digital era. Competitive advantages such as better products or lower prices may no longer be effective in addressing issues like customer defection due to low switching costs and numerous alternatives. A stable cooperative relationship can be established only when firms engage in value co creation with customers through service exchanges and mutual support as the actors evolve into cooperative assets. The sustainability of the cooperative relationship is greater than that of the customer relationship. This is because when customers are viewed simply as passive value recipients they can effectively switch different firms or brands.

3.2.3. BDA and Services Marketing

In their paper, Saradhi Motamarri, Shahriar Akter and Venkat Yanamandram argue that frontline employees (FLEs) play a dual role as “voice of the firm” to the customer and “voice of the customer” to the firm. The FLEs need to adapt their service to suit the individual customer needs and thereby enhance the customer’s service experience. In high contact services, like financial, healthcare and airlines, FLEs need to deal with every other customer differently as the interactions are highly personal and variable in nature. Detailed information about customers and their path to service facilitate FLEs to adapt the service in an optimal fashion. BDA may provide insights about the customers’ preferences and market conditions, which facilitate service adaptation. In doing so, while synthesizing the extant literature, the paper explores the challenges of FLEs to: enhance service delivery, support informed customers, achieve mass-customization, and build deeper relationships with customers. From the perspective of FLEs, the role and necessity of BDA differ from one service type to another. For example, delivering a financial consultation is resource- and time-intensive in comparison to processing a withdrawal request at a teller counter. In recognition of this, the research develops a service typology to explore the research questions. Similar to variations in customers and service types, there exist variations among FLEs and it is vital to recognize their typology as well. In addition to these variations, firms also vary according to their maturity in deploying BDA across their business functions. One of the findings of this research is that all these typologies intricately interact and influence BDA and impact the service delivery capabilities of frontlines. However, the review has identified significant knowledge gap in enabling the FLEs with BDA tools. Reconciling such shortcomings from the service-dominant logic perspective, it implies that managers ought to enhance the skill asymmetry between their frontlines and customers so that providers sustain their service portfolio. It also suggests that managers need to devise training programs to enable frontlines. Frontlines are to be oriented with customer linking and market-sensing capabilities and empower them to make adaptive decisions in real time. Ultimately, the better the frontlines deliver service, the better organizations sustain in the competitive markets. Lastly, both firms and customers also need to be aware of the privacy and ethical concerns of big data.

3.2.4. BDA and Marketing Capabilities

From a resource based theory perspective, the value of a resource is ultimately determined by its contribution when combined with other resources into unique, higher-order resource bundles (Jüttner and Wehrli, 1994). Such bundles form a strategic resource as it accounts for a significant portion of the firm's investment base, and is not freely available in factor markets (Clemons and Row, 1991). For strategic resources to become a source of competitive advantage, they must be leveraged by capabilities in organizational processes that create value for the firm (Barney and Hesterley, 2012; Kozlenkova et al., 2014). A capability is a special type of resource that enables the firm to leverage other resources advantageously in organizational processes to create value (e.g., Barney and Hesterly, 2012; Eisenhardt and Martin, 2000). Specifically, capabilities are a complex set of skills and routines deeply embedded organizational processes and routines (Day 1994). As such, capabilities are path-dependent (Kogut and Zander 1992), causally ambiguous (Lippman and Rumelt, 1982; Reed and DeFillippi, 1990), and embedded in context (Granovetter, 1985), and therefore costly or impossible to trade, imitate, or substitute (Dierickx and Cool, 1989; Peteraf, 1993). Therefore, capabilities are potential sources of competitive advantage.

Thus, in the big data environment, according to Waarden et al. (2016) big data resources which include big data technology resources, big data analytics skills and organizational big data resources is leveraged by marketing capabilities which in turn provides for better firm performance, and is thus a source of a competitive advantage for the firm.

Marketing capabilities are defined as the firm's ability to understand and meet customer needs better than competition, and to effectively deliver its products and services to customers (Day, 1994; Krasnikov and Jayachandran, 2008). Firm-level, strategic marketing capabilities encompasses eight distinct lower-level, operational marketing capabilities (Vorhies and Morgan, 2005). Four of them are related to transforming resources into product and services based on the firm's marketing mix processes that include pricing, product development, channel management, and marketing communications. Three other marketing capabilities (market information management, marketing planning, and marketing implementation) are used to manage marketing mix capabilities and resource allocations related to their execution. Finally, selling capabilities are processes carried out to obtain customer purchases (Vorhies and Morgan, 2005).

More specifically, big data resources enables firms to gain market insights, continuously sense and act on market changes that are critical to execute marketing capabilities successfully (Day 2011). Firms are thus able to tap into customer opinions, understand customer behavior, and converse with customers unlike traditional one way marketing (Chen et al. 2012; Day 2011).

Marketing capabilities are crucial to understand customers and to deliver offerings that match their needs, and is therefore a key driver of firm performance. Marketing capabilities are rare, valuable, non-substitutable, and imperfectly imitable and thus have potential for superior performance and competitive advantage (Vorhies and Morgan, 2005).

Based on the results of their study, Waarden et al. (2016) first advise managers to direct great effort to make sure that all aspects of the firm's overall big data asset are sufficient. In particular, firms should not focus solely on their technological big data infrastructure, or on the recruitment of data scientists. An organizational culture that discourages big data can seriously undermine its utilization that cannot be compensated for by excelling in big data analytics skills, for example. They also urge management to take immediate corrective action if inadequacies in any of these dimensions are observed.

Finally, Waarden et al. (2016) find that marketing capabilities is the critical link between big data resources and firm performance. Therefore, practitioners should ensure that big data resources are properly aligned with the firm's marketing processes and recommend that managers assess the feasibility of big data resources in the context of their application to support marketing capabilities. To achieve this, managers should regularly measure the effectiveness of big data projects on different marketing processes by identifying and using the most appropriate customer, market and financial performance metrics.

3.2.5. BDA Value, Customer Satisfaction and Firm Performance

Raguseo & Vitari (2018) examine the forms of business value that companies can create from big data analytics investments, the direct impacts it has on the financial performance of a firm, and the mediating effects of customer satisfaction. Firm performance includes both financial and market performance. Financial performance refers to revenue growth and profitability, while market performance is more about improving a firm's position against its competitors (Mithas, Ramasubbu, and Sambamurthy 2011; Tippins and Sohi 2003).

Resource based view, identifies business value as its central construct, between rare, inimitable and non-substitutable resources and firm performance (Kozlenkova, Samaha, and Palmatier 2014; Melville, Kraemer, and Gurbaxani 2004). In line with this conceptualization of resource based view, the results of their study (Raguseo, Vitari, 2018) suggest that first a higher business value, and then a higher firm performance are empirical indicators of the competitive advantage that arises from big data analytics solutions.

The positive relationship between customer satisfaction and financial performance has been widely discussed (e.g., Chi and Gursoy 2009). An increase in customer satisfaction could, for example, improve customer loyalty, which in turn generates higher cash flows. Customer satisfaction could be an important mediator between the business value of big data analytics solutions and the financial performance of a firm (Chumpitaz and Paparoidamis 2004).

An increase in customer satisfaction can be related to an improvement in the understanding of what customers want, via a big data analytics solution, so that the loyalty of customers is increased and, in return, future cash flows are enhanced. Firms could attempt to use big data to increase customer satisfaction (Wamba, Ngai, et al., 2017).Thus, Raguseo & Vitari (2018), based on the findings of their research, assert that customer satisfaction could be an important mediator between the business value of big data analytics solutions and the financial performance of a firm.

3.3. Big Data and Supply Chain Management

BDA can work across all SCM levers, conveying information from one area to another but the aggregation requires accuracy, timeliness, consistency and completeness (Hazen et al., 2014). For instance, marketing captures and tracks demand through Point of Sale (PoS) data, transportation creates records from GPS transponders, RFID data identifies stored goods and electronic data interchanges ends automatic buying orders.

Marketing has transformed customer knowledge into an agile system that sends large amount of information flowing upstream in the chain (Jüttner et al., 2010). Intimacy with customers can be achieved through increasingly more sophisticated methods of analysing customer data, and at this lever, data sources that include social media, mobile apps, or loyalty programmes can be found; all of them are the enablers for the sentiment analysis. Similarly, recording omnichannel sales information can be facilitated by the electronic and cloud PoS, and by machine generated data that record transactions. Butner(2008) stated that customer inputs need to be better aligned to SCM systems, and that supply chain managers have a tendency to focus more on their suppliers than their customers, but for our interest, he also reflected that technology has made it more feasible than ever to access and understand customer data, as Big Data enables sensing of social behavior (Shmuelietal., 2014).

Procurement deals with the relationships at the upstream supply chain. Data complexities on this side might arise from globalised purchasing strategies with thousands of transactions. In this lever, a strong connection with internal finance reporting led to adopt measures on spend visibility data, to achieve granular levels on aggregated procurement patterns. Nevertheless, according to Ainsworth (2014), data on external expenditure, which can be more than 50% of a company's cost, are "often backward looking, often inconsistently categorised and not integrated with internal costs". A subgroup of data that is still to be fully integrated and appears in the taxonomy as semi-structured are the business documents (purchase orders, shipping notices, invoices) sent through the EDI. Still et al.(2011) concluded that the procurement needs to activate the data sources not only for spending data management process, but also for the entire procurement function.

Warehouse management (particularly inventory management) has been radically changed by modern identification systems after successful introduction of RFID. Within this group, the largest clusters of data are related to an automated sensing capability, especially as the Internet of Things and extended sensors, connectivity and intelligence to material handling and packaging systems applications evolved. Position sensors for on-shelf availability share space with traditionally SKU levels and BOMs.

Transportation analysis applying Operational Research models has been widely used for location, network design or vehicle routing using origin and destination, logistics network topology or transportation costs as "static" data, as described by Crainic and Laporte (1997). New alternatives to manage and coordinate in real time using operational data rely on mobile and direct sensing over shipments that are integrated into in-transit inventory, estimated lead times based on traffic conditions, weather variables, real time marginal cost for different channels, intelligent transportation systems or crowd-based delivery networks among sources of Big Data. A detailed analysis of the 3 Vs in transportation data revealed to be the lever with proportionally higher speeds in data transition.

3.3.1. Benefits and Challenges of Big Data Driven Supply Chain

Big data is more useful than many people fully realize. Companies wanting to increase efficiency and profitability in supply chain execution should utilize big data. Benefits of big data driven supply chain are described as follows (Tahiduzzaman et al., 2017):

Improved visibility across supply chain: Planning and scheduling are perhaps the most crucial part of any supply chain. So much money can be lost or expended with scheduling and planning but using big data, firms can truly optimize this process. With the use of big data firms can gain end to end visibility so that managers know that where items are at all times, firms can also attain high quality decision support which can be crucial if something goes wrong a split second decision does not have to go without support.

Improved customer experience: Analysis of more different data types, including social media data, can be used to improve the customer experience.

Increased accuracy in demand forecasting: Another benefit is that a firm can really predict and satisfy demand. Analysis of big data helps to predict and determine what items are going to be needed as it pertains to demand.

Better manufacturing efficiencies: Big data helps to expedite order picking and order fulfillment by analyzing data from different sources like historical orders, item inventory, warehouse layout and historical picking times. It also improves product and service traceability. Identification of potential problem suppliers is executed in a better way. It uncovers defects in products/services in the supply chain, gives early warning and avoids recalls. Big data analytics can minimize inventory and supply chain risk.

Opportunities to solve more complex distribution network problems: Most complex distribution networks have developed organically over time into an almost impenetrable web of factories, warehouses and distribution hubs which can struggle to adapt quickly to changing patterns of demand. Companies can deal with this complexity more easily than in the past with the use of big data analysis. Big data provides the opportunity to solve much more complex distribution network problems by modelling outcomes in more detailed scenarios than ever before.

Better inventory planning and development: This is another benefit as big data allows users to plan, forecast, and truly optimize their inventory so that they do not waste space or waste money with items that may or may not be working the way they should.

Greater collaboration in supply chain stakeholders: Big data helps to better visibility which can translate into better collaborations with vendors, suppliers, carriers, distributers, warehouses, and customers.

The issues and challenges in adopting big data analytics for supply chain can be broadly categorized into two categories such as organizational challenges and technical challenges (Arunachalam, Kumar, & Kawalek, 2017).

Organizational challenges are listed as:

Time-consuming: Factors such as the volume of big data, complexity of supply chain and interpretation goals for the datasets along with external factors such as lack of access to data contribute in making the analytics process time-consuming.

Insufficient resources: For better results, the availability of real-time data is crucial. Supply chain being a platform that generates complex cross-functional data for interlinked entities, collection and storage of cross functional data should be streamlined.

Privacy and security concerns: Data sharing across a Supply Chain Network is a major factor in collecting data from various sources, analyzing it and giving insights. Although, regional or global Supply Chain Networks might face difficulties in sharing data across its different sources due to various Privacy, Security laws concerned with sharing of data. Lack of shared data in such cases can affect the accuracy of the insights that big data analytics might generate.

Behavioral issues: Due to the variety and volume of big data, there is an increased risk of decision makers identifying irrelevant correlations but statistically significant relations with insignificant causal linkage.

Issues with Return on Investment (ROI): Volume and variety of the big data collected makes it difficult to estimate the value of the collected data. Performing analytics on big data requires a significant amount of investment for building the infrastructure. Due to the uncertainty on value of the data, there is an increased risk on the returns that the investment on infrastructure might produce.

Lack of skills: The complexity of big data generated from supply chain source requires a combination of good domain knowledge analytics skills and the ability to interpret the usability of data. According to surveys, such a combination along with experience is difficult to find.

Technical challenges are listed as:

Data scalability: Issue of data scalability is considered a major technical issue in the process of utilizing big data analytics in any system. Inability of organizations to shift from traditional limited databases to distributed databases or cloud storage databases affects the insights from Big Data Analytics as the amount of relative data is compromised.

Data Quality: Quality of the stored and utilized data can affect the performance the results of the analytics techniques. Data being intangible and multidimensional based on its sources and applications. Dimensions of multidimensional dataset can be classified as intrinsic and contextual. For consistent and reliable results for decision making purposes, the quality of data should be consistent. The variety of data and type of sources for data in supply chain may affect the quality of the collected data.

Lack of techniques: Incapability of a firm to utilize the data affects the robustness of the insights developed after analyzing the datasets. The techniques used to analyze, compute, forecast and visualize need to be altered or upgraded in accordance to the complexity or volume of data (Arunachalam et al., 2017).

3.3.2. Big data and Procurement

Procurement can usually be defined as a process encompassing the identification and evaluation of user requirements, verification of suppliers' ability to meet these needs, development of agreements with those suppliers, implementation of ordering mechanisms, confirmation that payment occurs promptly, and evaluation of suppliers' performance, all of which are driven by a specific procurement strategy and objectives (Monczka, Handfield, Guinipero, & Patterson, 2010; Van Weele, 2009).

A comprehensive view of the different phases of the procurement process is presented by Luzzini, Longoni, Moretto, Caniato, and Brun (2014), who distinguish between the following:

• Strategic sourcing (Chen, Paulraj, & Lado, 2005; Leenders, Fearon, Flynn, & Johnson, 2002; Monczka et al., 2010), which involves procurement strategic decisions such as the decision to make or buy a product, definition of general procurement policies, reverse marketing, spend analysis and portfolio approaches, and supplier relationship management.

• Sourcing (van Weele, 2009), which pertains to tactical choices such as definition of the specifications of products or services to purchase, requests for quotations, supplier evaluations, negotiation, and selection.

• Supply (van Weele, 2009), which pertains to operational activities such as order placement, expedition, receiving and control, invoice reconciliation, and payment. Planning activities related to production are not included in this phase.

Strategic sourcing

The case studies selected by Moretto, Ronchi & Patrucco (2017) for their research highlighted that big data has the highest potential value for strategic sourcing. In terms of procurement strategy, a company noted the importance of sourcing planning and forecasting. Analytics can support identification of the best planning strategy to implement by using structured data such as bills of materials and price histories as well as unstructured data such as social media and web information. These decisions answer three questions: where, when, and how supplies should be obtained. The importance of analytics instruments increases exponentially with the number of variables that must be included in the planning activity. For instance, without the support of analytics, evaluating the best supply planning strategy for a product composed of several sub-components that can change over time may become an overwhelming task. Big data analysis might also identify correlations and trends among variables and the prices of goods and services. The price of business travel, for example, might be statistically correlated to the class of travel, route, airline, and number of days in advance the trip was booked. These analyses support the definition of specific travel policies based on statistical evidence. A similar approach might also be applied to the correlation between the price of components, services and utilities, and commodity prices, providing the opportunity for price hedging strategies. Forecasting techniques have been developed to foresee market conditions and determine the likely outcome of incoming demands. They have rarely been adopted at other stages of the internal supply chain. However, they can be used in other departments, including the procurement department, especially for long-term decisions regarding procurement timing and quantity. Statistical methods can be widely employed to predict future economic conditions to inform strategic long-term decisions, such as the inventory of finished goods (Ketter, Colling, Gini, Gupta, & Schrater, 2012). New models aim to predict future supply forecasts using not only structured data but also unstructured data collected from the Internet and social media. For example, a company that participated in the research started collecting data from the web to inform supply forecasting for travel management, but it is also planning to investigate how unstructured data might be considered.

Several companies addressed the value of a risk management approach. Traditionally, risk management has been based on structured internal data generated by the firm, collected inside the ERP system, and made available to closest suppliers. However, an uncountable amount of potential sources of information are available through the Internet. These sources can be paired with a traditional analytics framework to explore new ways to extract business value. The availability of new big data architectures has enabled the storage of a huge amount of data that could not be collected before due to management costs. A company addressed the importance of using big data to incorporate sustainability and financial information into risk analysis. It adopted big data on the one hand to report actual situations in the supply base regarding financial stability and, on the other hand, to predict future situations. The selected company mentioned that significant investments in sustainability indicate financial stability, which is incorporated into predictive models of analysis. This result is consistent with the literature addressing the key role of big data in early detection of possible supply disruptions (e.g., Chan et al., 2015; Wang et al., 2013).

Another important area in which big data could have high value is reverse marketing. A company that participated in the research utilizes data regarding the prices proposed by suppliers all over the world to make the best decision. Internally, they implemented a system similar to Booking.com's: based on big data, the system suggests the most convenient supplier for a specific procurement category. The purpose is twofold: to investigate existing suppliers and better understand how they are currently working and to determine the best available options, especially concerning efficiency and cost. The company of case study addressed potential value not only from the perspective of price but also from the perspective of innovation. Through this system, they are able to detect opportunities for innovation concerning the most frequently purchased items and use this unstructured information to highlight the main trends in the market and consistently revise the supply base.

The third important area in which the adoption of big data analytics has notable potential is spending analysis in the procurement department. Concerning analysis of spending and review of costs, buyers must have control over spending, and know how much and with whom they are spending their money. Big data can support employees responsible for procurement by providing reporting tools that can segment spending and highlight how the amount of goods procured can be rationalized. For example, a company adopted structured big data from a combination of internal and external sources of data for travel management. Through this analysis, before negotiating with suppliers, the company was able to identify problematic areas and fragmentation of spending among different suppliers. By rationalizing its spending, it was able to determine new practices to be implemented, with an expected savings of 6%.

Contract management can be improved as well, mainly through a better reporting approach. In the case of complex and burdensome contracts, procurement activity cannot be limited to the signature moment, but the agreed-upon conditions and expiry dates have to be continuously monitored in order to avoid disruptions that may have a huge impact on procurement performance and the company as a whole. Big data can provide information that is necessary to manage complex contracts. For example, a company used it to simultaneously compare conditions for complex contracts, thereby improving the management of internal processes.

Sourcing

Cross-case analysis identified the key contributions of big data analytics in the sourcing phase (Moretto, Ronchi & Patrucco, 2017). First, big data can support supplier evaluation by monitoring supplier performance. This result is consistent with the literature (e.g., Razi et al., 2014; Soloukdara & Parpanchi, 2015). Supply quality is usually assessed by internal controls for items received from the suppliers. However, random sampling is intended to guarantee the minimum standard and is only a proxy for the effective quality of the products. With the introduction of sensors for detecting specific product characteristics, it would be possible to implement tight quality controls. Moreover, in the last few years, companies have become more and more aware of the possibilities for generating value through the procurement department. One of these possibilities involves exploiting the company's relationship with its supplier in order to foster opportunities for innovation. When big data are employed within the procurement process, in other departments, the focus shifts from pattern recognition to outlier research. Indeed, the detection of opportunities for innovation is one case in which research about outliers can create value opportunities. In the past, a company adopted a vendor rating system for yearly supplier evaluation based primarily on structured data collected directly by suppliers. Recently, however, it introduced a pilot system that integrates data from external sources to complete the evaluation. Structured data with both reporting and predictive purposes are used, whereas only unstructured data with a reporting purpose collected through external sources were used in the previous system.

In terms of negotiation and selection, informative tools for determining negotiation strategies are some of the most powerful instruments at buyers' disposal during negotiation activities. The more valuable information that a buyer is able to collect about a supplier, the higher the buyer's bargaining power will be during the negotiation. The number of information sources has increased in the last few years, and consequently, the potential of big data has expanded. For example, selected company stated that, nowadays, it is increasingly difficult to find areas with inefficiencies, so in order to find new ways to extract value from procurement, it is important to use additional information to better define the negotiation strategy. The last domain in which those responsible for procurement can rely on big data is supplier selection. When a company engages with a new supplier, every single piece of information about the supplier is important—not only figures from financial statements or other public data but also unstructured data, including newscasts, papers, social media posts, and information on the Internet, are valuable sources that should be surveyed. New technologies enable not only “hard analysis” of the operative and financial performance of suppliers but also evaluation of “soft” features, like reputation.

As expected, according to Moretto, Ronchi & Patrucco (2017), all the phases of the procurement process would benefit from the adoption of a large amount of structured data with both reporting and predictive purposes.

The main benefits for companies are related to cost and time. Due to the higher amount of available data, companies can make decisions more efficiently. However, it is not only a matter of efficiency; the quality of the procurement process might improve as well because more available information reduces the amount of errors that occur. Big data involves digital processes, documents, and data, which improves the overall reliability of the decision-making process, especially regarding contract management and supplier selection, as large amounts of information can be compared, reducing errors and increasing the quality of output. Moreover, in terms of risk management, improved ability to detect problems in the supply base increases the flexibility with which the procurement process can be managed, such as when looking for an alternative supplier or implementing a supply mitigation strategy.

Basing supplier selection, monitoring, and control on more data and information can also improve procurement performance at the supplier level. As mentioned above, the main benefit is cost reduction; however, better knowledge about the supply market and suppliers’ cost structure leads to further negotiations and lower prices. In addition, big data available over the web or in other media allows companies to increase their scouting capabilities, thus leading to new—and, eventually, cheaper—opportunities in the supply market. Improvement in cost performance is the most cited benefit of big data in the sample; the companies introduced big data mainly for indirect types of procurement in order to improve efficiency and savings. However, today, procurement involves considerations other than savings. Suppliers are evaluated based on a wide spectrum of parameters, consistent with their strategic importance. Thereby, other types of performance might be improved, such as innovation potential, which is determined by reverse marketing and deeper monitoring of supplier performance, enabling identification of potential innovative processes.

3.4. BDA and Decision making

Based on literature review, BDA can also create value by improving organizational decision making.

3.4.1 Data Driven Decision Making Capability Framework

Hall et al. (2015) following the process-based entanglement approach of conceptualizing capabilities, they propose a data-driven decision making capability framework that is composed of data governance capability, data analytic capability, insight exploitation capability, performance management capability, and integration capability. This data-driven decision making capability framework coincides with Bernhardt's (2000) data intersections and the inquiry cycle, which includes establishing the desired outcomes, defining the essential questions, collecting the targeted data and organizing it, making meaning of the targeted data, taking action based on the targeted data, and assessing and evaluating the actions taken (Rallis & MacMullen, 2000). Each capability in the framework coincides with different steps of the data-driven decision making process.

Decisions should be made based on high-quality, well-organized data, or managers may make faulty decisions based on unrelated factors (Davenport et al., 2001). High quality data is an important prerequisite of data-driven decision making, and organizations' willingness to adopt data-driven decision making also increase their need for data governance (Kumar et al., 2013; Parssian et al., 2009). Without data governance with clear data quality policies, data quality management processes, data quality responsibilities etc., analytics tools and business models cannot contribute to organizations' data-driven decision making (Buhl et al., 2013). In their study (Hall et al., 2015), data governance capability refers to the ability of an organization to "provide data to users with the appropriate levels of accuracy, timeliness, reliability, security, confidentiality, connectivity, and access and the ability to tailor these in response to changing business needs and directions" (Mithas et al., 2011, p. 238). Some elements of data governance capability are data collection, data integration, data quality, and data access. Data collection reflects an organization's ability to collect data from different sources, data integration refers to an organization's ability to aggregate data from different sources or in different format, data quality refers to an organization's ability to manage the quality of data, such as data cleaning, data standardization, and data access reflects an organization's ability to transfer the proper data to certain people who have the authority to get access to the data.

Analytics refers to the generation of knowledge and intelligence from data to support decision-making and strategic objectives (Goes, 2014). Kim et al. (2005) posited that analytic capability can provide high quality analytical models and methods for managers and thus facilitate their data-driven decision making. In their study (Hall et al., 2015), data analytics capability is defined as a firm's capability to evaluate and interpret the collected data or information, which in turn combines with existing information to generate knowledge and intelligence to support decision making and strategic objectives (Bernroider et al., 2014; Goes, 2014). Goes (2014) summarized some elements of data analytics capability: decision time, analytics, and techniques. Decision time refers to whether the analytics is performed in real time, hourly, weekly, monthly, or yearly (Goes, 2014). Goes (2014) also summarized four types of analytics: visualization, exploration, explanatory, and predictive. Techniques reflect the analytics methods or models, such as statistics, econometrics, machine learning, computations, linguistics, optimization, and simulation, that an organization has (Goes, 2014).

Organizations do not need to collect and mine data to obtain insights if they do not exploit the insights obtained from data analytics (Davenport et al., 2001). Data-driven insights should be applied to business process and decision making routines in order to benefit organizations (Shanks & Bekmamedova, 2012). Insights should be transformed into action, such as modification of core processes such as strategic planning and daily operations (LaValle et al., 2011; Mitechell, 2006). In their study (Hall et al., 2015), insight exploitation capability is defined as an organizations' ability to harvest and incorporate insights into their decision making across core business processes such as guiding manufacturing, supply chain, software development, financial, and other important activities (Brown & Duguid, 1998; Mithas et al., 2011; Zahra & George, 2002). Mithas et al. (2011) summarizes several important processes such as manufacturing, supply chain, software development, financial, and other important activities. Similarly, LaValle et al. (2011) reported that top analytic performers apply analytics to financial management and budgeting, operations and production, strategy and business development, sales and marketing, customer service, product research and development, general management, risk management, customer experience management, brand and market management, workforce planning and allocation. There are six commonly discussed core business processes: manufacturing/operations activities, marketing activities, customer service activities, enhancing supplier linkages, sales activities, and financial management and budgeting.

In their study (Hall et al., 2015), performance management capability refers to the ability to develop a systematic and appropriate monitoring, evaluating, and control approach to observe and measure business performance, and then guide managerial actions accordingly upon the outcome (Lockstrom et al., 2010; Mithas et al., 2011).

Finally, integration capability is defined as a firm's ability to combine some or all of the previously distinct and interdependent assets, structures, business processes, system, and people, either inside the same party or of different parties, into a unified whole (Tanriverdi & Uysal, 2011). Integration capability has mainly three categories: IT infrastructure integration capability, process integration capability (Angeles, 2009; Rai et al., 2006), and people integration capability. IT infrastructure integration capability refers to the degree to which a focal firms has integrated its IT infrastructure for the consistent and high-velocity transfer of information within and across its boundaries (Angeles, 2009; Rai et al., 2006), process integration capability reflects an organization's ability to integrate its information flows among different parties both inside and outside of the organization (Angeles, 2009; Rai et al., 2006), and people integration capability refers to an organization's ability to maintain the real-time communication and collaboration among its employees or with outside partners.

3.4.2. BDA and Decision Making Effectiveness

The motivation of Cao, Duan & Li's study is to develop an understanding of the mechanisms through which BA improves decision-making effectiveness. Their study has based on prior BA literature, the information processing view and contingency theory to develop a path model to conceptualize and examine relevant concepts pertaining to BA and its impact on decision-making effectiveness.

More specifically, in addition to the idea that BA is an important factor for the development of a data-driven environment underpinned by contingency theory, their research drawing on the information processing view further supports that creating a data-driven environment in an organization will help improve the organization's information processing capabilities and ultimately data driven decision making and its decision-making effectiveness.

Based on the information processing view and BA studies (Davenport et al., 2001; Kiron et al., 2012; Lavalle et al., 2011; Kiron, Shockley, 2011), information processing capabilities of an organisation can be defined as its capacities to capture, integrate and analyse data and information, and use the insights gained from data and information in the context of organisational decision-making.

Lavalle et al. (2011) suggest that "for analytics-driven insights to be consumed—that is, to trigger new actions across the organization--they must be closely linked to business strategy, easy for end-users to understand and embedded into organizational processes so action can be taken at the right time". Similarly, it is argued that it is vital to develop an "analytically driven strategy" (Davenport, Harris, 2007), relevant business processes (Barton, Court, 2012), and organisational structure (Acito, Khatri, 2014) so that BA can be embedded into organisational practices thereby to improve decision-making and decision-making effectiveness. Otherwise, "a company will not know on which data to focus, how to allocate analytic resources, or what it is trying to accomplish in a data-to knowledge initiative" (Davenport et al., 2001). Thus, in order for an organisation to use BA effectively to create business value, a data-driven environment must be created by developing specific organizational strategy, policy, structure, and business processes to support and enable BA activities (Davenport et al., 2001; Kiron et al., 2012; Lavalle et al., 2011; Kiron, Shockley, 2011).

Accordingly, data-driven decision-making can be defined as the extent to which an organisation is open to new ideas that challenge current practice based on data-driven insight; has the data to make decisions; and depends on data-based insights for decision-making and the creation of new service or product (Kiron et al., 2012; Lavalle et al., 2011; Kiron, Shockley, 2011). Hence, decision-making effectiveness can be specified as the extent to which a company is more effective than its competitors at making real-time decisions, responding to change, and understanding customers, based on (Eisenhardt, Zbaracki, 1992; Rajagopalan et al., 1993).

Prior BA studies (Davenport et al., 2001; Kiron et al., 2012; Lavalle et al., 2011; Kiron, Shockley, 2011) suggest that the application of BA in an organisation is likely to enhance the organisation's abilities to process data and to use the insights derived from that data to make effective decisions, thereby to improve organisational performance.

However, the causal link from BA to information processing capabilities is much more complex than this direct relationship could describe. Prior BA studies have indicated that in order for a business to benefit from BA, simultaneously the business needs to develop a data driven environment to support BA applications (Watson, 2014; Davenport et al., 2001; Kiron et al., 2012; Lavalle et al., 2011; Kiron, Shockley, 2011). It can be expected that an organisation with a higher degree of fit between its BA and data-driven environment will outperform those with lower degree of fit; and the better the fit, the stronger the information processing capabilities.

Regarding how this fit influences information processing capabilities, a mediation model of fit can be supported by the proposition that technology can be an important determinant of organisational processes and structure in research underpinned by contingency theory (Jelinek, 1977). For example, Woodward argues that increasing technological complexity would require greater structural complexity for effective performance, while Thompson & Bates (1957) suggests that technology can be a determinant of organisational processes and structure. Alternatively, Perrow (1967) examines the relative routineness of work and advocated that organisational structure depends on technology. In line with this, it can be argued that BA applications are likely to bring about a data-driven environment embedded in and reflected by explicitly developing organisational strategy, policy, structure, and business processes to guide and enable BA activities, which will help develop information processing capabilities.

Therefore, in order for an organisation to meet its big data processing needs, it must develop its information processing capabilities through effective BA applications, which are enabled by developing an "analytically driven strategy" (Davenport, Harris, 2007) and designing relevant business processes (Barton, Court, 2012) and organisational structure (Acito, Khatri, 2014).

When an organisation has developed strong information processing capabilities to match its data processing requirements, the organisation can be expected to have sufficient information and data-driven insights to allow it to evaluate its business practices, to make informed decisions not only to improve internal business efficiencies but also to create new products or services for customers (Davenport, 2013), to achieve faster cycle times and greater flexibility (Davenport, 2006), and/or to significantly improve its performance (Galbraith, 1974). This is consistent with the strategic decision-making research. For example, it is expected that when a business has complete and accurate information about the relationship between choices and outcomes, it will be most likely to make successful decisions (Rodrigues, Hickson, 1995), to generate viable organisational strategies (Dean, Sharfman, 1996), and to improve organisational performance (Mueller et al., 2007).

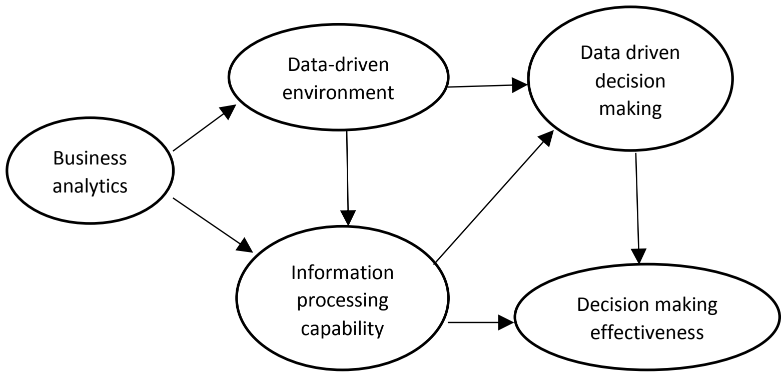

Fig. 2: BDA and Decision Making Effectiveness (Duan, Cao &Li)

Furthermore, it has been widely recognised in the BA literature that the potentials of BA can only be realised when a data-driven environment is developed so that decision making, strategy, and operations rely on data-driven insights (Davenport, Harris, 2007; Kiron et al., 2012; Lavalle et al., 2011). A data-driven environment is seen to help a company to have the data to make decisions, to be open to new ideas, to make decisions depending on fact-based insights, and to use fact-based insight for the creation of new service or product. Thus, it is finally proposed by Cao, Duan & Li that a data-driven environment is positively associated with data-driven decision-making which in turn affects positively decision-making effectiveness.

In their study, Sumbal, Tsui et al. (2017) try to explore the relationship between big data and knowledge management. Knowledge management is a well-known term, and it is almost an integral part of every organization in current world that is based on the knowledge economy. In the literature, knowledge management is considered as a process which involves various activities with four major activities: creating, storing, transferring and applying knowledge (Alavi and Leidner, 2001). Similarly, Bassi (1997) explains knowledge management as the process of creating, capturing and using knowledge to enhance organizational performance.

Big data analytics help in understanding and extracting valuable knowledge from the huge volumes of data, through the application of analytics and this knowledge then can be used for enhancing the performance of many different processes in an organization. Thus, the aim of big data and knowledge management is almost same which is to enhance an organization’s overall performance and gain competitive advantage (Grant, 1996).

Effective decision-making, which is one of the goals of knowledge management, is also now performed through the use of knowledge generated from big data analytics which provides evidence of the relationship between knowledge management and big data (Murdoch and Detsky, 2013). According to Bose (2009, p. 157), decision-oriented analytic application for big data helps in decision-making and thus can be termed a knowledge management initiative in which the organization’s best practices for each decision making process are pushed to the desktops of end users as embedded logic within analytic applications.

Another goal of knowledge management is to integrate and analyze the information from different perspectives for valuable decision-making (Lamont, 2012). Similarly, organizations also want data to be consistent and in an integrated form because then it is easier to extract knowledge from it (LaValle et al., 2013). Analysis of big data from multiple sources for decision-making is clearly in line with this goal.

An effective knowledge management system discards unneeded information, makes the right information available at right time to those who need it and focuses on people who can give value and act upon the valuable information (Cowley-Durst, 1999). In the big data analytics context, the first step is automated learning through “machine learning” algorithms to identify non-obvious, hidden patterns of information in data that have potential of creating knowledge. Then the second step is to test and confirm these relationships and this involves “human learning” and human insights to understand, revise and confirm or reject these relationships (Hair, 2007). Then, the insights of experienced employees is most of the time necessary to better understand and decide on the results obtained through big data. The final decision is made using the knowledge of these experts which is tacit knowledge (Nonaka and Takeuchi, 1995) which is one of the most important concepts in knowledge management. Therefore, another aspect of big data and knowledge management linkage is the combination of tacit knowledge of experienced employees (Ball, 2011) with the explicit knowledge obtained from big data (Feblowitz, 2013). Explicit knowledge is structured knowledge that can be documented, categorized and easily transmitted to others (Duffy, 2000), whereas tacit knowledge resides in the heads of people and is relatively difficult to be codified (Gore and Gore, 1999).

Sumbal, Tsui et al. (2017) provide an explanation of the relationship of big data and knowledge management. Knowledge creation and learning occurs through conversion between tacit and explicit knowledge in four modes, i.e. socialization, externalization, combination and internalization. Thus, first, explicit knowledge is generated through data, then this predictive knowledge is analyzed and transformed into tacit knowledge gained by employees during decision-making process to decide on what to do. Then, after the decision is implemented, the obtained results are then further discussed by the experts, thus going through the socialization cycle. In the after-action review process, i.e. what went right and how to perform the task next time, codification of the obtained knowledge (externalization) takes place to be used in future. This codified knowledge is integrated with the existing explicit knowledge obtained through analysis (combination). This stored knowledge or the explicit knowledge sources are then further used and learned by data scientists to refine or modify their existing tacit knowledge (internalization).

3.4.3 BDA and Strategic Decision Making

Strategic decision making (SDM) is the process of creating organisational mission and objectives and choosing the courses of action to achieve those goals (Eisenhardt and Zbaracki 1992). Based on sophisticated information technologies (Davenport 2013), BA offers the possibilities for organisations to use data-driven insights to improve their SDM and performance (e.g., Kiron and Shockley 2011; Bernhut 2012; Gillon et al. 2014). Thus, Cao & Duan (2015) investigate the mechanisms through which BA improves SDM and organisational performance.

From the affordance perspective, BA features offer the possibilities for data analysis and decision support at a basic level to an organization. In other words, BA provides only basic affordances that are the enabling conditions for exercising other higher-level decision-making affordances.

Decision-making affordances include identifying problems and opportunities, defining strategic objectives and criteria for success, developing and evaluating alternatives, and prioritising and selecting one or more alternatives, drawing on Simon (1947). Based on prior literature on contingency theory regarding the relationship between technology and organisational form and function, Cao & Duan (2015) take the view that a data-driven culture mediates the relationship between BA and decision-making affordances. For example, Woodward’s (1958, 1965) influential research on manufacturing technology and organisational structure suggested that technology can be an important determinant of organisational forms and functions.

While a number of different perspectives on SDM can be differentiated (Hutzschenreuter and Kleindienst 2006), rational and intuitive processes are frequently contrasted by prior studies (e.g., Khatri and Ng 2000; Dhami and Thomson 2012). Rational processes are characterised by decision-makers gathering appropriate information, developing possible alternatives, evaluating the alternatives and selecting the best possible alternative (e.g., Eisenhardt and Zbaracki 1992; Rahman and de Feis 2009). In line with this view, strategic decision comprehensiveness refers to the extent to which an organisation attempts to be exhaustive and inclusive in making and integrating strategic decisions (Fredrickson and Mitchell 1984; Atuahene-Gima and Haiyang 2004).

However, for decision situations where problems are ill-structured and complete, accurate, and timely information is not available, intuitive SDM offers a valuable alternative (Simon 1987; Khatri and Ng 2000; Kutschera and Ryan 2009). Intuitive SDM depends on "holistic hunch and automated expertise" (Miller and Ireland 2005). While seen as an effective approach to SDM, a number of studies have warned that intuitive processes need to be used cautiously (e.g., Khatri and Ng 2000; Miller and Ireland 2005) because it can be dangerously unreliable in complicated decision situations (Bonabeau 2003).

First, Cao & Duan (2015) argue that a data-driven culture developed in an organisation would facilitate its SDM comprehensiveness, drawing on BA studies. Davenport (2006) argued that a data-driven culture would inspire a companywide respect for measuring, testing, and evaluating quantitative evidence, while Kiron and Shockley (2011) suggested that companies with a data-oriented culture are characterised by data-driven leadership, analytics used as a strategic asset, and strategy and operations guided by analytical insights. Similarly, Ross et al. (2013) stated that organisations with a data-driven culture follow practices such as establishing one undisputed source of performance data, giving decision makers at all levels timely feedback, and consciously articulating business rules based on data. Thus, it is conceivable that a data-driven culture encourages organisations to conduct systematic analysis of available data to make strategic decisions.

Second, according to Cao & Duan (2015), an organisation is expected to be able to significantly improve its SDM comprehensiveness when it has realised its decision-making affordances. As discussed previously, BA enables organisations to effectively capture, integrate and analyse data. This means that the accuracy, sophistication, and completeness of rational analysis will be significantly improved (Molloy and Schwenk 1995). BA does not make decisions but input from BA can help make better decisions (Bell 2013). Using the data-based insights to provide input to decision-making, decision-making affordances enable organisations to use rational decision processes to systematically identify business problems and opportunities, define strategic objectives and criteria for success, develop and evaluate alternatives, and select the best alternative. SDM literature suggested that in business a successful decision is most likely when sufficient information is available (Rodrigues and Hickson 1995) and viable organisational strategies can be generated based on complete and accurate information about the likely relationship between choices and outcomes (Dean Jr and Sharfman 1996).

Third, SDM literature suggested that rational processes are preferred when data is available and reliable; otherwise, intuitive processes should be a better choice. A few prior studies demonstrated that there is a statistically significant negative correlation between rational and intuitive processes (SadlerSmith 2004; Elbanna et al. 2013). However, this does not mean that rational and intuitive processes are mutually exclusive; actually, a number of studies suggested that rational and intuitive processes should be used to complement each other at the same time (Robey and Taggart 1982; Sadler-Smith 2004; Coget and Keller 2010). In line with the above, Cao, Duan (2015) argue that, in the context of BA, the need for intuitive SDM, while it remains important, will be reduced since data availability has been significantly improved, and data-driven insights so gained can be used to provide input for more comprehensive SDM.

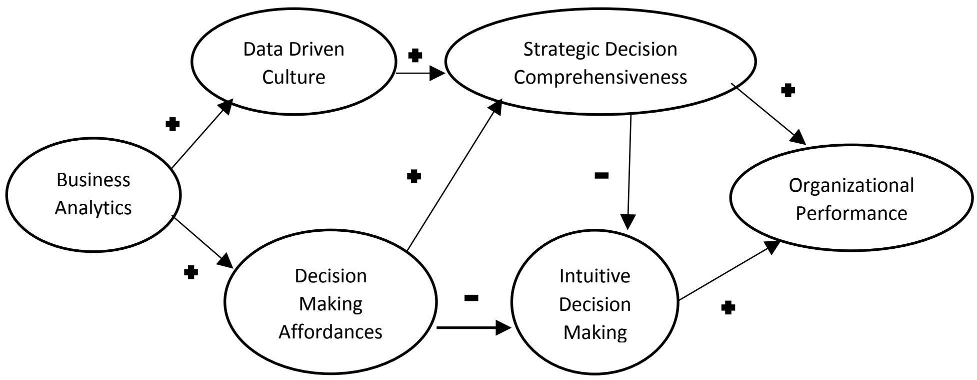

Fig. 3: BDA and Strategic Decision Making (Duan & Cao, 2015)

Finally, prior empirical SDM studies suggested that there is a complex relationship between SDM and organisational performance. While some studies suggested comprehensive process leads to better organisational performance (e.g., Eisenhardt and Zbaracki 1992; Miller 2008), others demonstrated that with an unstable environment there is a consistently negative relationship between comprehensiveness and organisational performance (e.g., Mintzberg 1973; Fredrickson and Mitchell 1984). Regarding the performance impact of intuitive SDM, prior empirical SDM studies showed mixed results as well in various research contexts (e.g., Khatri and Ng 2000; Elbanna and Child 2007; Dayan and Elbanna 2011). Drawing upon the literature on SDM and BA, Cao & Duan (2015) take the view that organisational performance can be improved since BA can provide unprecedented data-driven insights that in turn will significantly improve SDM.

4. Converting BDA Investments to Value

BI&A can be a strong source of improved business performance (Ransbotham and Kiron 2017). However, organizations often realize differential benefits when implementing them. Scholarly investigations of BI&A use among practitioners report inconsistencies in the relationship between BI&A and firm performance. Although some report significant financial gains (Watson et al. 2006; Wixom et al. 2008), others have failed to fully realize the anticipated benefits (Phan and Vogel 2010). Some organizations actually report a decline in competitive performance after implementing BI&A (Kiron et al. 2011). Thus, firms have to take into consideration several factors in order to realize the full potential of big data analytics.

4.1. BDA and Strategy

According to Mikalef & Krogstie (2018), under different patterns of contextual factors the significance of big data analytics resources varies, with specific combinations leading to high levels of incremental and radical process innovation capabilities.

The principle of context awareness has been identified as a key perspective for successful BPM implementations (Brocke, Schmiedel et al., 2014). This perspective is rooted in contingency theory (Donaldson, 2001), which assumes that there is not one universal best way to manage business processes, but rather, that management practices and resources should fit the organization and the external environment (Brocke, Zelt, Schmiedel, 2016).

Mikalef & Krogstie (2018) assert that a significant contextual factor is the goal of the organization, since goals directly influence the business process management practices and resources that are most suitable (Brocke, Zelt & Schmiedel, 2016). Several authors make the distinctions between exploitation and exploration, or else incremental and radical process innovation capabilities (vom Brocke, Seidel, Tumbas, 2015; Rosemann). Since the process of developing either incremental or radical innovations differs fundamentally, managers need to select and adapt their approach depending on the goal, thereby constituting the focus as an important contextual factor. Mikalef & Krogstie (2018) also suggest that another contextual factor that has to be taken into consideration is the external environment of the organization. Particularly, the uncertainty of the environment is critical to consider since under such conditions organizations need to reconfigure the way they operate and emphasize more on analytical and research capabilities. Finally, according to Mikalef & Krogstie (2018), an important group of contextual factors relate to the organization itself. Based on contingency theory, the size of the organization plays an important role since, typically, larger organizations require more formalized processes that cross vertical and horizontal functions than smaller firms (Brocke, Zelt, Schmiedel, 2016). Finally, type of industry is considered to be an important contextual factor, since practices and resources that may be effective in one industry may not be the most suitable in another (Trkman, 2013).

Thus, according to Mikalef & Krogstie (2018), different combinations of big data-related resources have a greater or lesser significance depending on the context and the type of process innovation capability they are targeted towards. More particularly, authors find that more technological and technical resources contribute towards delivering incremental process innovation capabilities, whereas a firm wide data-driven culture and strong managerial data analytic skills are critical in order to enhance radical process innovation capabilities. These results suggest that managers should develop different strategies in relation to their big data analytics initiatives, depending on the types of business process innovation they aim to achieve, while also taking into account the contingencies of the environment and the organization. Specifically, when a firm aims to achieve radical process innovation, data governance practices should encourage the breakdown of organizational silos and promote the notion of data-driven decision-making at all levels of the organization (Mikalef, Van de Wetering & Krogstie, 2018). In addition, managerial knowledge on data-driven initiatives and the potential application of big data to organizational problems should be encouraged through targeted seminars and training. Contrarily, in order to achieve incremental process innovations, managers should focus on technical excellence in terms of human skills and tangible resources. For these types of process innovations, strong technical skills are required, since gaining insight to produce incremental improvements likely requires expertise in skills that are domain specific.

Based on resource based theory, it is proposed that internal business processes could be important factors linking analytics capability and firm performance. Analytics capability business strategy alignment which is defined as the extent to which analytics strategies are aligned with the overall business strategy of the organization is one of the important aspects of internal business processes. The results of Akter, Wamba et al. (2016) study illuminate the significant moderating impact of analytics capability- business strategy alignment on the big data analytics capabilities and firm performance relationship.

Strategy receives an increasing amount of attention in the big data environment because business opportunities and other sources of macro and micro environmental change can easily be identified in this context (Constantiou and Kallinikos, 2014; George et al., 2014). According to Davenport et al. (2012, p.46), "[a] key tenet of big data is that the world and the data that describe it are constantly changing, and organizations that can recognize the changes and react quickly and intelligently will have the upper hand". Due to the unpredictable nature of big data, strategy researchers have always emphasized establishing the strategic fit or alignment, viewing the firm as a collection of resources, interlinked by a specific governance structure (Peteraf, 1993). Akter, Wamba et al., (2016) assert that alignment between BDAC and business strategy depends on visionary leadership which helps to synchronize capability with the functional goals and objectives, including marketing and operations management. For example, McAfee and Brynjolfsson (2012, p. 66) state that "companies succeed in the big data era not simply because they have more or better data, but because they have leadership teams that set clear goals, define what success looks like, and ask the right questions. Big data's power does not erase the need for vision or human insight". According to the authors (Akter, Wamba et al., 2016), larger amount of synchronization between BDAC and business strategies increases the synergy among different functional units and positively impacts firm performance. As a result of greater synchronization in the big data environment, it is possible to leverage BDAC by overcoming cognitive, structural and political challenges.

However, even though alignment has received increased attention in the BDA literature (Davenport, 2006; McAfee and Brynjolfsson, 2012), not enough is known about the impact of ACBSA on BDAC–FPER relationship. Illuminating the importance of ACBSA, Barton and Court (2012) state that, "[m]any companies grapple with such problems, often because of a mismatch between the organization's existing culture and capabilities and the emerging tactics to exploit analytics successfully. In short, the new approaches don't align with how companies actually arrive at decisions, or they fail to provide a clear blueprint for realizing business goals". Therefore, ACBSA is a distinctive capability which allows firms to link overall capability with firm performance. ACBSA also has the characteristics of a strategic organizational capability that can help firms match resources with changing market opportunities. In addition, it helps to align resources with market dynamics aided by multidimensional capability. The main way through which BDAC can help organizations achieve firm performance is by aligning capability with the strategic plan. As ACBSA is a strategic capability, it depends on a firm's ability to implement and leverage other capability resources (Bharadwaj, 2000b). This argument indicates that ACBSA influences the relationship between BDAC and FPER. A high level of organizational (i.e., BDA management), physical (i.e., IT infrastructure), and human (e.g., analytics skill or knowledge) resources could enable firms to align their business strategies to achieve high sales growth, market share growth, profitability, and return on investment. In the absence of business strategy alignment with BDAC, there is every possibility of the firm's performance declining.

4.3. BDA and Agility: the Role of Fit

Agility which captures a firm's ability to identify and effectively respond to threats and opportunities with speed, is considered as a critical firm dynamic capability in modern business environment (Sharma et al., 2010). There is evidence that data analytics use can help organizations to be more agile. Thus, in their study, Ghasemaghaei, Hassanein & Turel, (2017) leverage dynamic capability theory to understand the influence of data analytics use as a lower order dynamic capability on firm agility as a higher order dynamic capability. However, not all companies investing in data analytics increase their agility from their investments in such tools (Chen, Chiang, Storey, 2012). Therefore, authors also draw on the fit perspective to suggest that data analytics' use impact on firm agility will only accrue if there is a high degree of fit between several elements that are closely related to the use of data analytics use.

Organizational agility is often conceptualized as being comprised of two facets: operational adjustment agility, and market capitalizing agility (Lu, Ramamurthy, 2011). Operational adjustment agility focuses on internal processes and the extent to which they can be quickly be adapted to changes in an organization's external environment (Sambamurthy et al., 2003). Market capitalizing agility, refers to a dynamic entrepreneurial mindset in setting strategic direction, and decision making under uncertainty (Sambamurthy et al., 2003). Both facets of agility focus on a continuous change; market capitalizing agility emphasizes on entrepreneurial mindset, while operational agility focuses on speedy implementation (Lu, Ramamurthy, 2011).

Data analytics use could enhance firm agility because it can help organizations to better and more quickly understand their markets, make timely business decisions and rapidly leverage opportunities by effectively analyzing data (Chen, Chiang, Storey, 2012). More specifically, Ghasemaghaei, Hassanein & Turel (2017) assert that the use of data analytics which caters to decision making speed and quality can increase market capitalizing agility because it increases a firm's ability to respond to changes by improving services/products to address changing consumers' needs in a timely fashion. Moreover, according to the authors (Ghasemaghaei, Hassanein & Turel, 2017), the use of data analytics can increase operational adjustment agility because it can help with the optimization and calibration of business processes within organizations allowing them to enhance their ability to quickly respond to changes in their environment in the right way, using optimal decisions, and at lower costs relative to their competitors.

In addition, based on the fit perspective, it is argued by Ghasemaghaei, Hassanein & Turel, (2017) that the stronger the match between data analytics tools and key related elements including data, tasks and people, the higher the chances that the use of such tools will result in increased firm agility.

Data-tools fit

Modern technologies can produce various types of data in different formats (Sharma, Reynolds et al., 2010). Data analytics tools should be able to fulfill the data analyses needs of users by making it easy to retrieve relevant data and execute the needed analyses. Thus, the choice of the right analytics tools for the type of data at hand is important in enabling firms to take advantage of the different types of data available to them (Ghasemaghaei, Hassanein & Turel, 2015). High levels of fit between data analytics tools and data allow the organizations to analyze all relevant data relatively quickly and effectively and be able to obtain faster, more precise and data informed decisions related to both improving services/products and optimization of business processes which makes them more agile through the use of data analytics (Ghasemaghaei, Hassanein & Turel, 2017). In contrast, when this fit facet is low it may take analysts more time to find a way to analyze the target data and in many cases they may simply postpone or avoid this task (Ghasemaghaei, Hassanein & Turel, 2017).

People-tools fit

Based on the fit perspective, there should be a good fit between individuals' competencies and their job requirements (Edwards, 1991). Based on this notion, Ghasemaghaei, Hassanein & Turel (2017) argue that there should be a good fit between the abilities of the users and the data analytics tools they use. Such a fit would allow employees to take full advantage of data analytics tools to enhance their understanding of the changing market and customer demands as well as the performance of their internal business process in relation to the same. This enhanced understanding is then reflected in their ability to respond to such changes better and faster making a firm more agile. In contrast, when this fit facet is low, employees may postpone or avoid the task with which they have difficulties, take longer time to execute it, or even make errors while executing resulting in wrong decisions or having to repeat it.

Tasks-tools fit

Finally, based on the fit perspective, there should be a good match between a firm's task requirements and the mechanisms used to support the execution of such tasks (Mintzberg, 1979). In the context of data analytics, firm tasks being undertaken should match the analytical mechanism afforded by the technology (Parkes, 2013). When this match exists, the tools can provide the information required for completing organizational tasks faster, and assist users with making faster and better decisions (Kang et al., 2013; Trieu, 2017) which results in improved agility. On the contrary, when fit between tasks and analytics tools is low, employees may waste time trying to execute a task using data analytics that are inappropriate for that task or may even get the wrong results resulting in wrong decisions or having to repeat tasks (Ghasemaghaei, Hassanein & Turel, 2017).

4.5. System and Information Quality

The resource based theory suggests that the potential of high performance is greater when various quality resources are developed inside the firm to generate firm specific value using in-house investments, resource complementarities and complex systems (Kaufman, 2015), illuminating the relationship between the excellence of resources and firm performance.

In their research, Wamba, Akter et al. (2016) explore the relationship between system and information quality, business value and firm performance. The findings of their study suggest that BDA system quality and BDA information quality will have a positive impact on business value from BDA, which in turn will influence the firm performance.

McAfee and Brynjolfsson (2012a) identify system quality as a necessary component of a big data strategy in order to handle the volume, velocity and variety of data. In addition, the quality of information in big data environment depends on a large extent on the quality of a system, which ensures business value and better firm performance since it is a foundation of good decision making and positive outcomes (Wamba, Akter et al., 2016).

Thus, according to Wamba, Akter et al. (2016) a good technological platform is not enough to deliver the desired levels of business value and improve firm performance, it is also important to ensure robust information quality. Thus, managers need to focus on both the quality of BDA system and information. Overall the findings of the study provide big data managers an understanding of how an individual quality dimension contributes to the formation of business value and firm performance.

The study (Wamba, Akter et al., 2016) also explores sub dimensions that are specific to the system and information quality of BDA platform, which provides solutions to the emerging challenges of analytics platform. System quality basically represents the technical aspects of an analytics platform, which are firm specific, developed over time and difficult to imitate. Five sets of qualities are identified in the literature: system reliability, system adaptability, system integration, system accessibility, system response time and system privacy in providing solid insights (Davenport et al., 2012a; Davenport and Harris, 2007; Fosso Wamba et al., 2015; McAfee and Brynjolfsson, 2012b). First, system reliability indicates the dependability of an analytics platform that managers can rely on a platform which is free from any disruption or interference (Nelson et al., 2005). Second, system adaptability refers to the extent to which analytics platform can be adapted to meet various needs in changing situations (Kiron et al., 2014; Nelson et al., 2005). Third, system integration refers to the ability of the analytics platform to integrate variety of data (i.e., transaction, clickstream, voice and video) (Davenport et al., 2012a; Kiron et al., 2014). Fourth, system accessibility measures the extent to which an analytics platform is accessible to managers, ensuring convenience and scalability (Davenport et al., 2012a). Fifth, system response time measures timeliness and promptness of the analytics platform (McAfee and Brynjolfsson, 2012b). Finally, system privacy refers to the extent to which the analytics platform is safe and there is no possibility of leaking private information (Barton and Court, 2012a).

Information quality is defined as an analytics resource because valuable and rare information establish competitive advantages in big data environment (Davenport, 2006; Schläfke et al., 2013). Authors define information quality as the completeness, accuracy, format, and currency of information produced by BDA. 'Completeness' indicates the extent to which the user perceives that BDA provides all the necessary information; 'accuracy' focuses on the perceived correctness of information; 'format' refers to the perception of how well the information is presented; and, finally, 'currency' refers to the user's perception of the extent to which the information is up to date (Wixom and Todd, 2005). For instance, BDA used in financial organizations combine data across various platforms in order to provide more complete information (Barton and Court, 2012b). In addition, it is also critical to ensure accuracy of information as BDA deals with data from multiple sources, which needs to be organized and processed. Information quality also focuses on formatting insights which could be done through filtering and better visualization of results (Wixom et al., 2013). Finally, currency of information should also receive attention because continuous flow and sharing of information help managers make real-time decisions (Davenport et al., 2012a).

4.6. Information Governance

Information governance is defined as a collection of competences or practices for the creation, capture, valuation, storage, usage, control, access, archival, and deletion of information and related resources over its life cycle (Mikalef, Krogstie, van de Wetering, Pappas, & Giannakos, 2018; Mikalef, Pappas, et al., 2017; Tallon, Ramirez, & Short, 2013). Weber, Otto, and Österle (2009) suggest that information governance encompasses activities relating to decision maker roles (structural practices), decision tasks (procedural practices), and person responsibilities and development (relational practices) (Tallon, 2013). Structural practices are responsible for determining key IT and non-IT decision makers and their corresponding roles and responsibilities regarding data ownership, value analysis, and cost management. Structural practices include, for instance, explicit declarations about the main roles of setting policies and standards for protecting and using data. They also can encompass the establishment of technical committees to oversee compliance with internal policies or with legal rules about data retention and resource management (Rasouli, Trienekens, Kusters, & Grefen, 2016). Operational practices are the means by which organizations execute information governance. These practices span a series of activities including data migration, data retention, cost allocation, data analytic procedures, and access rights. Finally, relational practices describe the formalized links between employees of the technical and business sides in terms of knowledge sharing, education and training, and strategic planning (Kooper, Maes, & Lindgreen, 2011).

Data governance is a complex undertaking and many data governance initiatives in organizations have failed in the past. According to Brous, Janssen & Vilminko-Heikkinen (2016), principles of data governance include organization of data management, ensuring alignment with business needs, compliance and a common understanding of data which are analyzed as follows:

Most researchers agree that data governance has an organizational dimension (Khatri & Brown, 2010; Otto 2013; Wende & Otto, 2007). For example, Wende & Otto believe that data governance specifies the framework for decision rights and accountabilities to encourage desirable behavior in the use of data. The first organizational dimension of Otto (2013) relates to an organization's goals. Formal goals measure an organization's performance and relate to maintaining or raising the value of a company's data assets (Otto, 2013). Functional goals refer to the tasks an organization has to fulfil and are represented by the decision rights defined such as the definition of data quality metrics, the specification of metadata, or the design of a data architecture and a data lifecycle (Weber, 2009). Otto's second organizational dimension is the organizational form, such as the structure in which responsibilities are specified and assigned, and the process organization. Issues are addressed within corporate structures (Wende, Otto, 2007). The data governance model is comprised of roles, decision areas, main activities, and responsibilities (Wende & Otto, 2007). However, the organization of data governance should not be seen as a "one size fits all" approach (Wende & Otto, 2007). Decision-making bodies need to be identified for each organization, and data governance must be institutionalized through a formal organizational structure that fits with a specific organization (Malik, 2013). Decision rights indicate who arbitrates and who makes those decisions (Dyché, 2007). According to Dawes, "stewardship" focuses on assuring accuracy, validity, security, management, and preservation of information holdings. Otto's third organizational dimension consists of a transformation process on the one hand and organizational change measures on the other. Malik indicates the need to establish clear communications and patterns that would aid in handling policies for quick resolution of issues, and Thompson et al. show that coordination of decision making in data governance structures may be seen as a hierarchical arrangement in which superiors delegate and communicate their wishes to their subordinates, who in turn delegate their control.

Data governance should ensure that data meets the needs of the business (Panian, 2010). A data governance program must be able to demonstrate business value, or it may not get the executive sponsorship and funding it needs to move forward (Smallwood, 2014). Describing the business uses of data establishes the extent to which specific policies are appropriate for data management. According to Panian, if used correctly, data can be a reusable asset as data is a virtual representation of an organization's activities and transactions and its outcomes and results. Data governance should ensure that data is "useful" (Dawes, 2010). According to Dawes, information should be helpful to its intended users, or should support the usefulness of other disseminated information. While government organizations may want to achieve the goals of data governance in theory, they often have difficulty justifying the effort unless it has a practical, concrete impact on the business (Panian, 2010). Data governance also provides the framework for addressing complex issues such as improving data quality or developing a single view of the customer at an enterprise level (Panian, 2010). Wende and Otto believe that a data quality strategy is therefore required to ensure that data management activities are in line with the overall business strategy. The strategy should include the strategic objectives which are pursued by data quality management and how it is aligned with the company's strategic business goals and overall functional scope. Data quality is considered by many researchers to be an important metric for the performance of data governance (Khatri & Brown, 2010; Otto, 2011; Wende & Otto, 2007).

Data governance includes a clearly defined authority to create and enforce data policies and procedures (Wilbanks & Lehman, 2012). Panian states that establishing and enforcing policies and processes around the management data is the foundation of an effective data governance practice. Delineating the business uses of data, data principles establish the extent to which data is an enterprise wide asset, and thus what specific policies are appropriate (Khatri, Brown, 2010). According to Malik, determination of policies for governance is typically done in a collaborative manner with IT and business teams coming together to agree on a framework of policies which are applicable across the whole organization (Malik, 2013). Tallon regards data governance practices as having a social and, in some cases, legal responsibility to safeguard personal data through processes such as "privacy by design", while Trope & Power suggest that risks and threats to data and privacy require diligent attention from organizations to prevent "bad things happening to good companies and good personnel" (Power, Trope, 2006 p. 471).

Mechanisms need to be established to ensure organizations are held accountable for these obligations through a combination of incentives and penalties (Al-Khouri, 2012) as, according to Felici et al., governance is the process by which accountability is implemented. In such a manner, accountability can unlock further potential by addressing relevant problems of data stewardship and data protection in emerging in data ecosystems.

According to Smith, governing data appropriately is only possible if it is properly understood what the data to be managed means, and why it is important to the organization. Misunderstood data or incomplete data requirements can affect the successful outcome of any IT project (Smith, 2007). Smith believes that the best way to avoid problems created by misunderstanding the data, is to create an enterprise data model and that creating and developing an enterprise data model should be one of the basic activities of data governance. Attention to business areas and enterprise entities should be the responsibility of the appropriate data stewards who will have the entity-level knowledge necessary for development of the entities under their stewardship (Smith, 2007). To ensure that the data is interpretable, metadata should be standardized to provide the ability to effectively use and track information (Khatri & Brown, 2010). This is because the way an organization conducts business, and its data, changes as the environment for a business changes. As such, Khatri & Brown believe that there is a need to manage changes in metadata as well. Data governance principles should therefore reflect and preserve the value to society from the sharing and analysis of anonymized datasets as a collective resource (Al-Khouri, 2012).

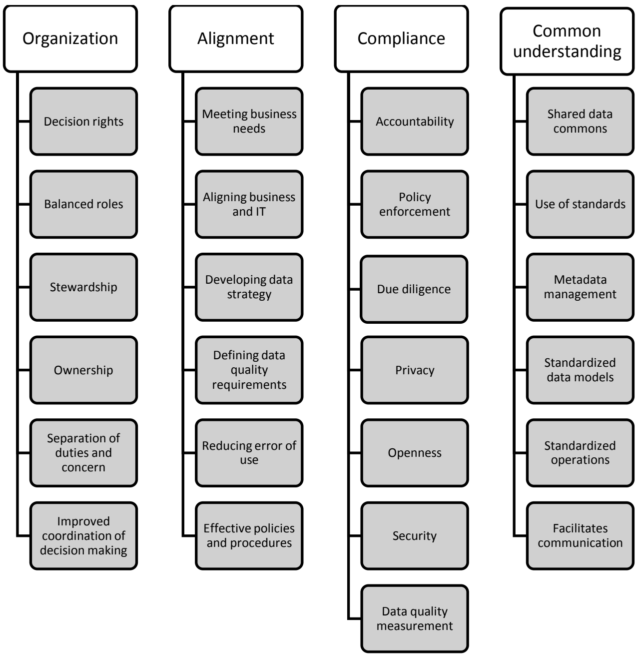

Fig. 4: Information Governance Principles (Brous, Janssen & Vilminko-Heikkinen, 2016)

Some factors can facilitate and accelerate the adoption and diffusion of data governance but others can act as inhibitors, slowing its adoption and use or perhaps preventing it outright (Tallon, 2013).

Tallon (2013) argues that organizations that have a focused business strategy tend to be more prepared to enact a standard set of data governance policies; those that are more diverse in their strategic orientation might struggle to find policies that are equally relevant to each aspect of their business. Organizations that can align IT and business strategy are more likely to agree on data governance because this alignment is often achieved through close cooperation between CIOs and business executives. Centralization can also play an enabling role as there is less need to allow business functions to enact their own policies or to try to reconcile potentially conflicting rules. Industry regulations push organizations to consider an appropriate system of policies rather than risk non-compliance penalties. IT standardization or data integration can make it even easier to devise common governance rules.

According to Tallon (2013), inhibitors of data governance come in various forms, but foremost among them are legacy systems that force organizations to manage multiple, disparate, and disconnected systems. It is more difficult to devise practices to protect and manage data when it is duplicated across the organization. A decentralized organization can find it difficult to create a common set of data governance policies or standards that will satisfy all decentralized users equally. Certain user behaviors can also limit the adoption of data governance. A pervasive packrat culture that fails to discourage the needless retention of data can be difficult to reverse. The breadth and complexity of an organization's product and service offerings can also inhibit the adoption of data governance. A multidivisional organization structured along product or market lines can complicate the adoption of standard data governance policies, with each division seeking exemption from a standard set of organization-wide policies by claiming that standard policies are incompatible with their idiosyncratic business needs. Where organizations have bowed to internal pressure to allow divisions to opt out of established firm wide policies in favor of personalized policies, the result has been a chaotic mix of complex and in many cases contradictory policies.

According to Tallon (2013), the assumption guiding data capture and retention has always been that big data's value must exceed its cost. However, this belief is rarely tested and without a clear sense of value and how it can shift over time, organizations are liable to make mistakes. This could lead to extreme levels of technical, economic, or reputational risk if organizations under-invest in storage technology for highly valuable data—for example, storing clinical trial data for a new blockbuster drug on an unreliable storage device would be relatively inexpensive but risky. Similarly, organizations could waste resources by over-investing in storage technology when the value of their data is low— for example, needlessly replicating data or using the most expensive and resilient storage device when a less expensive system would suffice.

The challenge facing organizations is to develop governance mechanisms that strike a balance between risk and reward in the face of growing quantities of data and innovation that delivers better, faster, and cheaper storage technology. These policies and structures should protect data from errant factors that could destroy or limit its value, but governance should not be so restrictive and intransigent that it prevents or impedes organizations from unlocking value from their data. Tallon (2013) suggests that data governance is a reflection of how organizations value their diverse and expanding portfolio of data assets as well as their desire to invest in storage technologies to protect those assets from various risk factors.

According to Tallon (2013), organizations readily capture and retain data that might yield little or no value in the near term but that could rise in value at some point in the future. In some cases, anticipation of value can be sufficient to justify data retention for extended periods of time even when doing so poses a risk to personal privacy. Retention can be justified if the costs of storing the data and safeguarding its privacy are less than the opportunity costs of not having the data available for future decision making or analysis. As such, managers might need to continually assess whether to retain data they believe could be valuable in the future— balancing the opportunity cost of not keeping the data against its retention costs.

Tallon (2013) mentions that the belief that storage is cheap and its cost is likely to decline further is true in terms of hardware prices, but it ignores a variety of other datacenter operating expenses that comprise the total cost of ownership. Other costs such as energy, maintenance, and software increase in direct proportion to the growth of big data. If users feel that the cost of retaining data is zero or close to zero, they will not be motivated to carefully decide what data to keep and for how long. Instead, there is an urge to keep as much data as possible on the basis that it might be useful in the future. Moreover, users are more likely to add to the glut of big data when they are not responsible for covering the costs of managing it. Without some form of chargeback, the actual cost of managing data will be forever hidden from users.

The simplest form of cost control within a big data environment is described as follows by Tallon (2013): organizations can use highly resilient, reliable, and accessible but expensive storage technologies for their most valuable data and less reliable or accessible but cheaper technologies for their relatively less valuable data and archives. Data can migrate from lower tiers to higher tiers as value rises. Organizations might be willing to accept the increased storage costs as value of data rises in order to be better protected. As value drops, the data can be migrated to a lower tier or perhaps even deleted entirely. Hence, the key to managing the cost of big data is to physically move or transfer it to a higher or lower tier each time there is a significant jump or decline, respectively, in its value.

4.6.1. Information Governance and Organizational Capabilities

Results of research conducted by Mikalef, Krogstie et al. (2018) show that information governance helps strengthen a firms' dynamic and operational capabilities, which in turn leads to competitive performance gains.

Specifically, Mikalef, Krogstie et al. (2018) mention that in the health care industry the provisioning of information led to reduced medical errors and an overall increase in efficiency. In the airline industry, information governance was linked to enhanced decision making in scheduling, market analysis, and ticket pricing. Information governance however is also an important element of delivering data-driven innovations. Kathuria et al. (2016) show that by developing a proficient mechanism of managing information-related artifacts, both incremental and radical innovations can emerge.

Effective operational capabilities are necessary for attaining and sustaining a competitive advantage. Marketing capabilities enable firms to better understand their customers' current and future needs and to be more capable of promptly serving these needs (Protogerou et al., 2012). Marketing capabilities positively affect competitive performance by creating customer satisfaction and loyalty and superior market performance (Hooley et al., 2015). Technological capabilities create competitive value by allowing a firm to transform input into output in an efficient and effective way while being able to avoid excessive costs, time, organizational disruptions or performance losses (Protogerou et al., 2012).

By strengthening its dynamic capabilities there are several mechanisms which lead to business and competitive value. Literature has placed particular emphasis to the potential of dynamic capabilities to increase innovativeness (Agarwal, Selen, 2009) and responsiveness to match/address changing environments and improve effectiveness (Drnevich, Kriauciunas ,2011; Mikalef, Pateli, 2017). First, dynamic capabilities can positively affect competitive performance by enabling a firm to identify and respond to opportunities, by developing new processes, products, and services (Makadok, 2001). Second, dynamic capabilities can improve the speed, effectiveness, and efficiency with which a firm operates and responds to changes in its environment developing as such, an organizational agility (Tallon, 2008).

While dynamic capabilities may produce competitive performance gains on their own right, it is suggested in literature that one of their mechanisms of action is by enabling, or strengthening, existing operational capabilities (Eisenhardt, Martin, 2000). This idea has been initiated by Eisenhardt's and Martin's argument, that dynamic capabilities are necessary, but not sufficient conditions for competitive advantage. According to this perspective, competitive performance does not rely on dynamic capabilities per se, but rather, on the resource configurations created by dynamic capabilities. Protogerou et al. (2012) also adopt this perspective, demonstrating that dynamic capabilities create value indirectly by changing operational capabilities.

Additionally, building on the growing importance of information governance as a means of attaining business value form big data investments, study by Mikalef & Krogstie (2018) examines how it influences a firm's dynamic capabilities, and how environmental factors impact these effects. More specifically, results show that big data governance has a positive and highly significant effect on sensing, seizing, and transforming capabilities that is magnified under varying combinations of environmental conditions.

Based on a qualitative research approach, Tallon et al. (2013) show that big data governance has effects in multiple areas which depend highly on the industry of examination. For instance, they note that in the airline industry big data governance was linked to enhanced decision making in scheduling, market analysis, and ticket pricing. These effects relate primarily to an increased capacity in the sensing of business opportunities and threats. Establishing big data governance practices allowed airlines to collect, store, and analyze data of greater richness and combine it with real-time data. Having done so meant that more accurate predictions could be made about forecasting demand, and consequently, could adjust prices, schedules, and marketing approached accordingly. A similar study of airline industry practices uncovered a different effect of big data governance on organizational processes. Delta, the American airline, manages more than 130 million checked bas per year. Recently, Delta has become the first major airline that allows customers to track their bags from mobile devices, utilizing as such their big data to develop novel services that provide customers with greater peach of mind (Delta, 2016). The big data governance practices established by Delta have enabled the company to identify that bag tracking is important for passengers, and capitalize on this opportunity by deploying novel solutions which foster better relationships with its customers. This example is one of many in which establishing a solid big data governance scheme can facilitate a firm's seizing capabilities. Another case of the value of big data governance is that in the healthcare industry. Sophia Genetics builds on artificial intelligence for data driven personalized medicine (Forbes, 2016). Sophia Genetics can read and aggregate the genetic code of DNA and predict and diagnose genetic diseases. The company also combines genome data with analysis, medical science and expert opinion to create diagnosis. Such examples in which big data result in transformations within companies and industries, and radically transform capabilities is common when solidi big data governance schemes are established (Alyass et al., 2015). In other words, to be able to develop such capabilities within the firm, a prerequisite is to have established solid big data governance practices (Loebbecke and Picot, 2015).

In addition, Mikalef & Krogstie (2018) refer that findings from previous studies show that the effect of big data governance has on dynamic capabilities is of increase relevance in conditions of high environmental uncertainty (Côrte-Real et al. 2017). The main idea is that big data governance is particularly relevant in contexts that are characterized by fierce competition, high complexity, and where there are limited resources (Mikalef et al., 2017b). In such contexts, being able to capture data from all departments within a firm, develop a firm-wide data-driven culture, and rapidly perform analytics or develop big data-driven solutions is of increased relevance and value, particularly in fostering strong dynamic capabilities (Wamba et al., 2017). Despite almost no reach examining the role of big data governance in variations of environmental conditions, anecdotal claims as well studies investigating the value of big data, demonstrate that under circumstances where there is uncertainty stemming from the environment, the realized value from solid practices is particularly discernible (Wamba et al., 2015). Thus, Mikalef & Krogstie (2018) develop this notion and distinguish between three different types of environmental uncertainty, dynamism, heterogeneity, and hostility (Newkirk and Lederer 2006).

In their study, Mikalef et al. (2018) suggest that big data analytics capabilities can enhance innovative capabilities and that information governance strengthens this relationship.

Information governance can be viewed as a framework to maximize the derived value from information within the firm, which requires a series of actions to effectively orchestrate and leverage related resources, and transform them into a big data analytics capability.

Structural practices are concerned with the systematic arrangement of people, departments, and other subsystems within the organization (Peppard & Ward, 2004). Early studies note that defining a clear structure and appropriate decision rights relative to data and information, is one of the key success factors, particularly in projects that span departmental and functional boundaries (Abbasi, Sarker, & Chiang, 2016).

Procedural practices include from what data will be gathered, stored, and analysed, to the skills of technical and business employees that are sought after in the market (Tallon et al., 2013). Procedural practices are vital in big data projects since they define how information governance is executed in different levels within the organization and at different inflection points of the information life cycle.

Finally, relational practices play a critical role in the formation of big data analytics capabilities since they define the roles and responsibilities of employees, and determine how they should be adapted based on organizational demands (Mikalef et al., 2018). Relational practices in the context of big data are responsible for aligning individuals with the goals of strategy.

A big data analytics capability can prompt innovation in multiple ways (Mikalef et al., 2018). First, incremental improvements in existing products or services through more detailed identification of customer feedback and real-time operational monitoring can be attained through a strong big data analytics capability (H. Chen, Chiang, & Storey, 2012). In addition, a BDAC can help firms develop opportunities for radical innovations, by deploying new products or services that can create new markets and create fundamental changes in the market and consumer behaviour (Erevelles, Fukawa, & Swayne, 2016).

It is commonly acknowledged that companies that share data internally and have a shared vision of the role of analytics in strategy gain more (Ransbotham & Kiron, 2017). Strong information governance practices facilitate data sharing, which in turn amplifies the effect on innovation (Tan, Zhan, Ji, Ye, & Chang, 2015). The main reason for this is because information governance dictates how data is shared, the quality of data and generated insights, as well as the formal procedures of communicating outcomes with executives of all domains (Lee, Kao, & Yang, 2014). The necessity of information governance is also highlighted by Tallon et al. (2013) since opening data and insight within and between organizations cannot work without structure, processes, and well-defined roles.

From a practical point of view, authors (Mikalef et al., 2018) suggest that by clearly defining the important structures, processes, and roles, the deficiencies can be easily spotted and targeted investments can be made. In addition, an information governance provides a sense of direction in terms of who does what, and what belongs to who which promotes data-driven logic in organizations and breaks down the impression, that big data analytics is a purely technical task.

4.7. BDA and Organizational Inertia

Over the last years, the scope and approach of most scholarly efforts concerning BDA primarily focus on infrastructure, intelligence, and analytics tools. However, these contributions substantially disregard other related resources, as well as how these socio-technological developments should be incorporated into strategy and operations thinking. Dealing with these particular and aligning all organizational and IT capabilities is thus considered to be one of the grand challenges ahead to get sustainable results from technological innovations, including BDA (Van de Wetering et al., 2017; Mikalef et al., 2017).

Van de Wetering, Mikalef & Krogstie (2018) define through which process stages firms have to go for big data analytics initiatives to add business value:

Strategic Initiation (Van de Wetering, Mikalef & Krogstie, 2018): The first phase is about the initiation of BDA within the firms. Firms usually have to identify strategic priorities and ask 'crunchy questions.' Therefore, this phase requires senior management involvement and a project champion that support this significant development. Part of this first phase is also the assessment of the current BDA capabilities. This particular assessment, by the judgment of the experts, is crucial for the identification of both the scope and requirements for BDA initiatives as well as the capabilities.

Use-Cases and Data-Driven Pilots: Based on authors' analyses (Van de Wetering, Mikalef & Krogstie, 2018), they identified a second phase, i.e., Use-cases and data-driven pilots. The first step in this second phase is the identification and definition of various 'Use Cases.' In this step, challenges within strategic focus areas are identified based on specific and explicit business need, ambitions, requirement and also possible suitability for BDA, i.e., 'the problem.' Various experts pointed out that these use cases should define 'the problem' relative to the foreseen analytical data lifecycle. After this, firms should, in essence, define a technical approach by identifying a suitable approach based on the data lifecycle, volume, variety, and velocity. Moreover, in this process, a clear distinction should be made between analytical techniques that scale up existing (analytic/data) assets and the once that provide the firm with new relevant data perspectives. It is suggested that this part of the Use Case is followed by the refining of a particular business decision based on analytic results. Outcomes suggest that a second sub-phase of the Use-cases and data-driven pilots phase, thus, concerns the roll-out of pilots and possible prototypes. This phase is an essential part of this phase as it could save valuable time and money for firms as firm target value providing initiatives. A key attribute for data-driven pilots is the involvement of the leadership. In this process firms should also seek for low-risk, high-value pilot projects as these might be able to contribute to the foundation for BDA capabilities while simultaneously cultivating early, and sustaining sponsorship.

Adoption and Maintenance: The final phase is about the adoption and maintenance of BDA initiatives. Authors (Van de Wetering, Mikalef & Krogstie, 2018) suggest that adoption situationally requires both organizational change and a robust technical environment should be maintained. Findings suggest that within this phase firms need to exploit talent, user skills, innovative technologies, and best-practices to continuous iterative exploration and investigation of past business performance to gain insight and drive business strategy. This step also links this final phase to the first one. So, outcomes suggest that for every type of big data solution firms need to embrace agility, while at the same time (technical) data governance needs to be in place to deliver business insights cost-effectively. What is understood from all the interviewees is that BDA capability transformations require both hard and soft skills and firm resources. Moreover, as most firms have been heavily investing in enterprise systems to streamline their processes and recently started cultivating a mindset that focusses on analyzing data and information to improve performance.

The process of adopting and diffusing big data analytics, as well as actions taken in response to generated insight, necessitate organizational transformation. As with any form of organizational transformation, there are multiple inhibiting factors that threaten successful change such as organizational inertia. Specifically, Besson & Rowe (2012) state that "inertia is the first level of analysis of organizational transformation in that it characterizes the degree of stickiness of the organization being transformed and defines the effort required to propel IS enabled organizational transformation".

Mikalef, Krogstie et al. (2018) suggest that inertia is present in different forms, including economic, political, socio-cognitive, negative psychology, and socio-technical.

Negative psychology inertia has been predominantly attributed to group and individual behavior, and is based on threat perceptions of losing power or even their position. Uncertainty about the role of individuals or groups in the face of novel technological deployments thus causes negative psychological reactions which biases them towards the status quo (Kim et al., 2009). Socio-cognitive inertia emphasizes mostly on malleability due to path dependencies, habitualization, cognitive inertia and high complexity (Lyytinen, Newman, 2008). These forms of inertia arise due to periods of sustained stability and routinization caused by a stable environment. Socio-technical inertia on the other hand refers to the dependence on socio-technical capabilities, which arise from the interaction of the social systems and technical system and their joint optimization (Rowe et al., 2017). Economic inertia may be present in the form of commitment to previously implemented IT solutions that do not pay off and create sunk costs, or through transition expenses which cause organizations to not adopt potentially better alternatives (Haag, 2014). Finally, political inertia is caused by vested interests and alliances which may favor that the organization remains committed to a specific type of information technology so that partnerships are not broken.

Mikalef, Krogstie, Pappas & van de Wetering (2018) suggest that inertia can be present at many phases of adoption and diffusion so action need to be taken throughout projects. The first stage is called intrapreneurship and experimentation, where the new technology is typically used informally by individuals within the IT department. Users usually have little to no knowledge on the new technology and learn through experimentation, or when the firm decides to invest in some employees with related skills. During this stage, individual experimenters work to gradually diffuse the technology throughout the organization and communicate its value. This stage can be initiated either by employees in the IT department, or by top management which sees the new technology as worth looking into.

The second stage is called order from chaos, in which different units within the organization gradually become accustomed to the new technology and are invited to participate in activities oriented towards its diffusion. The success of the technology at this stage largely depends on the establishment of formal rules, standards, and governance practices for the deployment and use of the technology.

The third and final stage is called institutionalization in which the new IT becomes part of the organizational fabric. The existence of governance schemes and rules also allows for the technology to reach a broader set of actors. In this stage it is common that there is a well-defined strategy on how the technology is used firm-wide along with a clear assessment of the expected business value. While these stages have been clearly defined in literature for different types of technological innovations (Mergel and Bretschneider, 2013), in the case of big data they are seldom referenced. One of the downsides of doing so is that firms expect that their investments will pay off before they have been completely assimilated within the organization, and without the presence of a solid strategy and governance for achieving business goals. Having defined these stages allows us to understand the inertial forces that dominate each one, as well how they can be overcome.

According to their study’s findings (Mikalef, Krogstie et al., 2018) economic inertia was a very prominent theme among most of the companies, especially those that were not multi-national firms or had major slack resources, such as micro, small, and medium enterprises. For large conglomerate companies, scarcity of economic resources towards the implementation of big data projects was not an issue. Specifically, in non-large companies’, economic inertia was present from the top management and board of directors, who had doubts about the value of big data analytics in their operations. Similar quotes were made by several other executives, showcasing that economic inertia are a major inhibiting factor of big data adoption and deployment. A major inhibitor that leads to this is the unclear link between big data investments and business value. On the other hand, competitive pressures seem to be driving mimetic behaviors in companies mitigating the effects of economic inertia.

Mikalef, Krogstie et al. (2018) also mention that socio-cognitive inertia was found to be a problem in most of the companies that were examined. In most of the cases, big data implementation meant that data from different departments needed to be gathered. This entailed that a detailed account of what data were available should be initiated, and in many cases new processes needed to be put into place to collect data. Typically, the IT department was responsible for starting this process, and had to explain to various other siloed departments their goals, ways of realizing them, and what their role would be. The different mental modes, use of language, and objectives caused conflicts that threatened and even greatly delayed big data implementation projects. In many cases, consulting firms were brought in to resolve this issue and act as a mediating agent. They tried to create a common understanding of the objectives of the big data projects, and bring representatives from each business unit to the table so that cognitive structures can be in alignment.

Political inertia was detected in several firms that had formed partnerships with other private and public organizations.

According to Mikalef, Krogstie et al. (2018), negative psychology was again observed mostly in small and medium firms, where the IT department comprised of a small number of employees. Primarily, it was found in personnel that had been actively employed for many years, in contrast to those that had recently graduated. These employees feared that the introduction of big data analytics and the corresponding technologies and tools for analyzing and visualizing data would render their skills as non-significant. Authors saw that the way many IT managers handled this issue was by providing their division with small challenges, and incrementally growing projects. Also, they assigned a few hours a week where they had the freedom to experiment with big data tools. This allowed them to try out these novel tools at their own pace, without the fear of time pressure to deliver results.

Finally, in terms of socio-technical inertia, Mikalef, Krogstie et al. (2018) observed that in many cases middle-level managers exerted behaviors that stalled the implementation of big data projects. Their primary fear was that decision-making would now reside in insight from analytics, therefore replacing them. In many occasions this fear manifested itself as a distrust towards the value of big data analytics, and general tendency to downplay the significance of big data in operations. Despite the clear directive of top management to diffuse big data analytics into operations, in many circumstances middle-level managers would not invest time in clear implementation strategies leaving the IT department with a bleak understanding of how they should proceed. Typically, these issues were resolved by a strong top management vision and leadership. In addition, training seminars for middle-level managers on the value of big data and their role were regarded as very beneficial in overall success.

5. Conclusions

5.1. Research Summary

Portion of literature is devoted to the relationship between big data and innovation. Four models of analytics in innovation were found: analytics as innovation, innovation on analytics, analytics on innovation and innovation through analytics (George & Lin, 2017). BDA capabilities support the two subsets of absorptive capacity: potential and realized (Al-Jaafreh, Fayoumi, 2017). More specifically, they support knowledge acquisition and assimilation (potential absorptive capacity) and knowledge transformation and exploitation (realized absorptive capacity). Absorptive capacity is inherent with knowledge capabilities and beneficial to organizational learning thereby facilitating innovation. In the Big Data Innovation Model the customer participates in the innovation process directly and deliberately or indirectly and unintentionally (Constantinides, Lorenzo 2015). Customer data is available through online interactions, transactions, social media activity and Internet of Things. Thus, effective use of this fast growing customer and market data contribute to product innovation in terms of novelty and meaningfulness (Cao & Duan, 2015) and service innovation through service automation and human-machine service practices leading to proactive, real time service provision and highly individualized and tailored services to customer's needs (Lehrer, Wieneke et al., 2018). It is also stated that BDA as the sensing and seizing components of dynamic capabilities contribute to firm performance by enabling improvements through efficiency and effectiveness on business processes (Torres, Sidorova & Jones, 2018).

Concerning marketing, firms provide digital platforms through which they can capture customer data enabling value co-creation (Xie, Wu et al., 2016). Proceeding to analysis of that data a firm can gain useful insights for customer's behavior and characteristics, consumer sentiment (consumers' feelings, perception and evaluation of products and services) (Sheng et al., 2017). This enhances firms' ability to understand and meet customer's needs better than competition and effectively deliver its products and services (Waarden et al., 2016). Based on these insights firms can advance marketing strategies such as personalized advertising, brand improvement and recommendation (Sheng et al., 2017). Use of BDA can deliver better customer experience and more competitive services (Xie, Wu et al., 2016; Motamarri, Akter & Yanamandram, 2017) resulting in higher customer satisfaction and retention which affects positively firm performance (Raguseo & Vitari, 2018).

Furthermore, there are many benefits of using big data analytics in supply chain such as improved visibility across supply chain, improved customer experience, increased accuracy in demand forecasting, better manufacturing efficiencies, opportunities to solve more complex distribution network problems, better inventory planning and development and greater collaboration in supply chain stakeholders (Tahiduzzaman et al., 2017). However, there are also organizational and technical challenges for a big data driven supply chain (Arunachalam, Kumar, & Kawalek, 2017). Additionally, regarding the value of big data in the procurement process it is argued that big data has the greatest potential impact on the strategic sourcing phase (mainly in terms of procurement strategy configuration, reverse marketing, and spend analysis) and the sourcing phase (mainly in terms of supplier evaluation, negotiation, and selection). Thus, the main benefits of companies are related to cost and time (Moretto, Ronchi & Patrucco, 2017).

The role of data analytics in decision making is also pointed out in literature. A data driven decision making capability framework is proposed which consists of data governance, data analytics, insight exploitation, performance management and integration capabilities that are necessary for defining the essential questions, collecting the targeted data, making meaning of the targeted data, taking action based on the data and evaluating the actions taken (Hall et al., 2015). It is advocated that business analytics is an important factor for the development of a data driven environment that improves organizations' information processing capabilities and ultimately data driven decision making and decision making effectiveness (Cao, Duan & Li). Moreover, combination of tacit knowledge of relevant staff with explicit knowledge obtained from big data improves the decision-making ability. It is also asserted that data driven culture improves decision making affordances promoting rational processes of strategic decision making. In other words, organizations are encouraged to conduct systematic analysis of available data and making decisions based on facts and reducing the need for intuitive strategic decision making (Cao & Duan, 2015).

There are conditions under which firms can turn big data investments into value. BDAC is an important enabler of enhanced firm performance, the improvement of which can be linked with dimensional and sub dimensional levels. The literature also highlights the significant moderating impact of analytics capability- business strategy alignment on the big data analytics capability-firm performance relationship (Akter, Wamba et al., 2016). In addition, different combinations of big data related resources have a greater or lesser significance depending on the context and firms' aim. Therefore, managers should develop different strategies in relation to their big data analytics initiatives depending on what they aim to achieve while also taking into account the contingencies of the environment and the organization (Mikalef & Krogstie, 2018). Data analytics use impact on firm agility will only accrue if there is a high degree of fit between several elements that are closely related to the use of analytics tools (data-tools, tasks-tools, people-tools) (Ghasemaghaei, Hassanein & Turel, 2017). Significance of quality dimension to the formation of business value and firm performance is also pointed out. In particular, system quality and information quality is foundation of good decision making and positive outcomes (Wamba, Akter et al., 2016). Information governance is a collection of structural, procedural and relational processes. Principles of data governance include organization of data management, alignment with business needs, compliance and a common understanding of data (Brous, Janssen & Vilminko-Heikkinen, 2016). Information governance helps strengthen firms' dynamic and operational capabilities (Mikalef, Krogstie et al., 2018). Finally, three process stages were found that firms have to go for big data analytics initiatives to add business value: strategic initiation, use cases and data driven pilots and adoption and maintenance (Van de Wetering, Mikalef & Krogstie, 2018). However, the process of adoption and diffusion necessitates organizational transformation which is inhibited by various forms of inertia including economic, socio-cognitive, socio-technical, political and negative psychology (Mikalef, Krogstie et al., 2018; Mikalef, Krogstie, Pappas & van de Wetering, 2018).

5.2. Suggestions for Future Research

There is an emphasis on the BA impact on innovation success from an information processing and use perspective, thus all the key factors affecting innovation success such as business strategy, management practices, human resource management, leadership, inter-firm networks are not captured. In addition, concerning service innovation, it is unlikely that account of the potential for service automation and human-material service practices is exhaustive (Lehrer, Wieneke et al., 2018). Future research could investigate whether additional uses emerge.

It is also necessary to explore how big data can collaborate in value co-creation processes in the context of multiple actors, besides only customers and firms (Xie, Wu et al., 2016). Future studies to yield valuable know-how for services marketing in leveraging big data analytics are also necessary. It is anticipated that a qualitative field study will help to portray the maturity of BDA and its influencing role on the frontline. There is a need of future work focusing on the development of a robust plan, so that firms are set to realize benefits from big data in enhancing their service delivery, and creating meaningful positive impact to the organization (Motamarri, Akter & Yanamandram, 2017).

To increase the volume and accuracy of the data generated from various processes such as manufacturing and logistics, improving the sensor accuracy in physical systems along with enhancements in the data integration technology amongst various business processes is necessary and can be a potential field of study for further research (Arunachalam, Kumar, & Kawalek, 2017). Furthermore, concerning big data usage in supply chain and more specifically in procurement process, additional research should aim to increase empirical research on the topic, perhaps with an action-based approach or through longitudinal case studies, in order to understand the horizontal implementation process of big data in different procurement departments (Moretto, Ronchi & Patrucco, 2017).

Factors such as top management team, organizational structure, and business environment may have a significant effect on strategic decision making and its outcomes. Thus, further research on the effect of business analytics on strategic decision making need to consider such organizational variables (Cao, Duan & Gendao). Further research is certainly required for a better understanding of the roles that business analytics plays in influencing both rational and intuitive decision-making across various decision contexts (Cao & Duan, 2015).

The measures of the three types of fit found in literature are rather static in nature. Since fit may change over time, future research can apply longitudinal designs to account for fit dynamics (Ghasemaghaei, Hassanein & Turel, 2017). Also, information quality insignificantly influences firm performance, indicating that perhaps there might be other variables affecting this relationship. Therefore, future research can explore the deep relationship between quality dynamics, business value and firm performance (Wamba, Akter et al., 2016). Additionally, although the importance of information governance on influencing firm organizational capabilities and, effectively, competitive performance is examined, a sensitivity analysis on contextual factors is not performed (van de Wetering, Mikalef & Helms, 2017). Theoretically, it is claimed that information governance and the affected capabilities would vary in significance depending on the dynamism of the environment (Mikalef, Pappas et al., 2016). Finally, regarding organizational inertia there is an emphasis on companies that have actually adopt big data, a more complete approach would be to look at what conditions cause other firms to not opt for big data. Second, while Mikalef, Krogstie et al. (2018) briefly touched on the issue of middle-level managers not following insight generated from big data, it is important to understand in more detail the decision-making processes that underlie their reasoning. Also, the actions that are taken in response to these insights are seldom put into question. This is a future area which should be examined since the value of big data cannot be clearly documented in the absence of knowledge about strategic or operational choices (Mikalef, Krogstie et al., 2018).

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