Analytics-Based Decision-Making for Service Systems:

A Qualitative Study and Agenda for Future Research

Abstract

While the use of big data tends to add value for business throughout the entire value chain, the integration of big data analytics (BDA) to the decision-making process remains a challenge. This study, based on a systematic literature review, thematic analysis and qualitative interview findings, proposes a set of six-steps to establish both rigor and relevance in the process of analytics-driven decision-making. Our findings illuminate the key steps in this decision process including problem definition, review of past findings, model development, data collection, data analysis as well as actions on insights in the context of service systems. Although findings have been discussed in a sequence of steps, the study identifies them as interdependent and iterative. The proposed six-step analytics-driven decision-making process, practical evidence from service systems, and future research agenda, provide altogether the foundation for future scholarly research and can serve as a step-wise guide for industry practitioners.

Keywords: Big data analytics, decision-making, service systems

1. Introduction

The discourse on big data analytics (BDA) and its associated opportunities and challenges show an incessant growth in both academic and practitioner literature, as stressed out by Frizzo-Barker, Chow-White, Mozafari, and Ha (2016). This emerging and fast-rising analytics momentum is closely linked to organizational opportunities such as, business intelligence and cognitive computing (Fan, Lau, & Zhao, 2015; Gupta, Kar, Baabdullah, & Al-Khowaiter, 2018), business innovation and data products (Thomas H. Davenport & Kudyba, 2016; Delen & Demirkan, 2013), customer churn prediction and sentiment analysis (Aswani, Kar, Ilavarasan, & Dwivedi, 2018; Grover, Kar, Dwivedi, & Janssen, 2018; Kumar, Mangla, Luthra, Rana, & Dwivedi, 2018; Ragini, Anand, & Bhaskar, 2018; Shirazi & Mohammadi, 2018; Singh, Irani, Rana, Dwivedi, Saumya, & Kumar Roy, 2017) knowledge co-creation (Acharya, Singh, Pereira, & Singh, 2018) or organizational agility(Popovič, Hackney, Tassabehji, & Castelli, 2018).

Service systems are everywhere, such as in retail, healthcare, financial sector, supply chain management, or hospitality, and yet little is known about how to leverage big data in service systems (D. Q. Chen, Preston, & Swink, 2015; Paul P Maglio & Chie-Hyeon Lim, 2016). Accordingly, this project focuses on service systems because the global economy is rapidly growing with services, which now contribute to more than 70% of the GDP (Akter, Wamba, & D'Ambra, 2019). BDA can play a leading role in today's service systems, which are capable of learning, adapting, and making decisions based on data collection, transmission, and processing to improve its response to a future occurring (Medina-Borja, 2015). The extant literature reports the use of BDA for service system innovation (Opresnik & Taisch, 2015) as well as better decision-making (Ghasemaghaei, Ebrahimi, & Hassanein, 2018; Zhong, Newman, Huang, & Lan, 2016). For example, Amazon increased its sales revenue by more than 30% through its big data-driven recommendation engine, Capital One increased its retention rate by 87%, Marriott enjoyed 8% more revenue through revenue optimization, and Progressive enhanced its market capitalization of over $19 billion by using real-time information, products and rate comparisons (Thomas H Davenport & Harris, 2017).

Following the success path of big service firms, small and medium organizations have started to invest heavily in BDA – however, these investments will only profit if BDA is integrated to the decision-making process (Côrte-Real, Oliveira, & Ruivo, 2017; de Vasconcelos & Rocha, 2018; Raguseo, 2018; Sharma, Mithas, & Kankanhalli, 2014; Yaqoob, et al., 2016). Overall, as stated by Dwivedi, et al. (2017), "innovation is vital to find new solutions to problems, increase quality, and improve profitability. Big open linked data (BOLD) is a fledgling and rapidly evolving field that creates new opportunities for innovation" (p. 197), and by focusing on analytics-based decision-making processes for service systems, this paper contributes to the current essential need to understand how to facilitate decision making through big open linked data. Despite the importance of BDA, many service firms still struggle to yield value from BDA initiatives (Kaisler, Armour, Espinosa, & Money, 2013; Power, 2016). According to Ransbotham, Kiron, and Prentice (2016, p. 4), "competitive advantage with analytics is waning. The percentage of companies that report obtaining a competitive advantage with analytics has declined significantly over the past two years". Specifically, little is known about the effective operationalization of BDA in business problem solving or decision-making (Elgendy & Elragal, 2016; Miah, Vu, Gammack, & McGrath, 2017). Motivated by this challenge, the main research question we address in this paper is the following one: what are the steps in the BDA-driven decision-making process in service systems?

To answer this research question, the paper aims to provide a general taxonomy of BDA-driven decision process in order to broaden the understanding of both business problem solving and decision-making based on a systematic literature review and qualitative studies. We present a six-step framework and discuss each step of the decision-making process in detail with examples coming from the service sector. The paper has been organized into four main parts. First, we introduce key concepts related to the study including big data, BDA, and BDA-based decision-making; second, we explain the methodological gestalt; third, we present the results of our systematic review and semi-structured interviews, and finally, we discuss the findings of the study with a future research agenda.

2. Literature Review

2.1. Service systems and big data

Worldwide, Services are becoming the dominant form of economic exchange (Fitzsimmons, Fitzsimmons, & Bordolai, 2014; Spohrer & Maglio, 2008). Services are now broadly considered to encompass all activities in which people, technologies, specialised competencies and capabilities work together and facilitate value co-creation for all the involved actors (Spohrer & Maggilo, 2010; Vargo, Maglio, & Akaka, 2008). Relying on these ideas, scholars have regarded that a 'service system is a value co-creating process that uses resources (people, technology, organization and shared information) to satisfy customer needs better than competition'(Akter, et al., 2019). Extending these views, Maglio and Lim (2016) define service systems as "configurations of people, information, organisations, and technologies that operate for mutual benefit." Information derived from BDA turns service systems smarter by facilitating learning, dynamic adaptation and decision-making under uncertainty (Lim, Kim, Heo, & Kim, 2018).

As one of the early adopters of BDA, service systems are constantly struggling to achieve competitive advantages using both structured and unstructured data. On the one hand, we refer to structured data as demographic data including name, age, gender, date of birth, address, and preferences. On the other hand, unstructured data refers to clicks, likes, links, tweets, voices, etc. Each day, we are creating 2.5 quintillion bytes of data, which is created by search engines (e.g., Google & others), social media (e.g., Facebook), digital photos (e.g., Instagram), services (e.g., Venmo, Uber and Spotify) and Internet of Things (e.g., voice devices) (Marr, 2018; Singh, Dwivedi, Rana, Kumar, & Kapoor, 2017). Overall, the challenge in service systems consists of dealing with both types of data so that we can generate meaningful insights for robust decision-making in this sector.

2.2. Big data and analytics

Big data can be distinguished from traditional data sets owing to its unique elements. Initial focus on big data characterized it using 3Vs – volume, variety, and velocity (e.g., H. Chen, Chiang, & Storey, 2012). Nowadays, big data is characterized by greater detail including 6Vs – volume, variety, velocity, veracity, value, and variability (Gandomi & Haider, 2015). The volume attribute of big data represents the mass quantities or magnitude of data. Companies collect sheer volumes of data from dynamic, heterogeneous, and ubiquitous resources and devices (Barnaghi, Sheth, & Henson, 2013) in order to make informed decisions (McAfee, Brynjolfsson, & Davenport, 2012). These diverse sources and devices enable to collect different ‘varieties’ of data including structured, semi-structured or unstructured (Gandomi & Haider, 2015). Velocity or the rate at which data are generated and should be analyzed and acted upon is a unique attribute of big data. Digitalization has accelerated data generation demanding real-time analytics that can produce decisional insights (Mishra, Luo, Jiang, Papadopoulos, & Dubey, 2017). Veracity refers to uncertainty and unreliability in some types of big data. Complexity, inconsistency and anonymity of large data sets can cause data to be unreliable (Sivarajah, Kamal, Irani, & Weerakkody, 2017). Variability relates to variation in the data flow rates that is mainly caused by the inconsistent velocity of big data (Gandomi &

Haider, 2015). Finally, the value of big data refers to its economic value that can be extracted from structured and unstructured data. Data in its original form is considered less valuable unless large volumes of data are analyzed using proper BDA methods (Mishra, et al., 2017).

BDA can be defined as a holistic process that involves the collection, analysis, use, and interpretation of data for various functional divisions with a view to gaining actionable insights, creating business value, and establishing competitive advantage (Akter & Wamba, 2016). BDA is becoming increasingly adopted and have become an urgent and essential property of enhancing business processes and outcomes. Impact of BDA on outcomes such as agility (Ghasemaghaei, Hassanein, & Turel, 2017), value creation (Seddon, Constantinidis, Tamm, & Dod, 2017), innovation (Marshall, Mueck, & Shockley, 2015), brand authenticity sentiments (Shirdastian, Laroche, & Richard, 2017), and business competitiveness (P. M. Lee, 2013) is noteworthy. Nevertheless, studies on BDA are still only nascent and BDA-based decision-making and problem-solving to the most part remain unexplored, requiring thereby further investigation (Côrte-Real, et al., 2017).

2.3. Analytics-based decision-making

In the current highly competitive business context, business intelligence, decision support, and analytics have become pillars of decision-making (Phillips-Wren et al., 2015). Decision makers are desiderated to make informed decisions, and BDA is capable of augmenting the traditional decision-making process (Elgendy & Elragal, 2016). The ability of BDA to deliver faster and better decisions through insights derived from multiple data sources has motivated BDA adoption (Janssen, van der Voort, & Wahyudi, 2017). Making accurate, timely and better decisions have not only become essential but a matter of survival in today's complex and competitive business context (Delen & Demirkan, 2013). Therefore, the necessity of more and better data, knowledge, and insights is more than ever.

Despite various opportunities BDA can deliver to organizations, the integration of BDA to the decision-making process still remains a challenge. Several scholars have discussed the big data process and its contents. For instance, Zhou, Chawla, Jin, and Williams (2014) identified six steps including: data collection, data storage, data management, data manipulation, data cleansing, and data transformation; and M. Chen, Mao, and Liu (2014) introduced three steps; data handling, data processing, and data moving. However, mechanisms or methods of BDA integration in decision-making process are still scarce (Bumblauskas, Nold, Bumblauskas, & Igou, 2017; K. H. Tan, Ji, Lim, & Tseng, 2017). The framework presented by T. H. Davenport (2013) provides a modest and effective way of dealing with such endeavor. The framework provides six steps of analytics-based decision-making: step 1: recognize the problem or the question, step 2: review previous findings, step 3: model the solution and select the variables, step 4: collect the data, step 5: analyze the data, step 6: present and act on the results. Although this framework depicts the decision process as a linear one, the steps are always iterative (T. H. Davenport & Kim, 2013); findings of one step can apprise a previous step.

3. Methods

This study follows a qualitative method based on both a systematic literature review, thematic analysis and semi-structured interviews. First, we followed a systematic literature review approach to establish rigor in discussing the BDA-driven decision process. This approach was based on similar efforts by Akter and Wamba (2016) and Thomas and Leiponen (2016) in BDA research and Benedettini and Neely (2012) in services research and Tranfield, Denyer, and Smart (2003) in management research (see Appendix-3). Systematic literature review is a useful approach to uncover, organize, and deduce proof relevant to a particular research question in a rational, transparent, and repeatable manner (Greenhalgh, Robert, Macfarlane, Bate, & Kyriakidou, 2004; Sivarajah, et al., 2017). In our effort to capture concrete, practical, and empirical evidence of BDA-driven decision-making in services organizations, application of systematic literature review method is rather appropriate and meaningful. The following sections describe the research protocol including the search strategy and publication selection criteria.

As the initial step, search strings were established to serve the purpose of the research. We identified relevant publications for the review using search strings that consisted the key words 'big data analytics*' with several other terms. Using wildcard symbols results in returning hits for other related key words such as 'big data analytic' and 'big data analysis'. The primary focus was given to BDA and decision-making, and hence, search strings 'big data analytics* AND decision-making', and 'big data analytics* AND decision-making' were deemed appropriate. In Davenport's (2013) six-step decision-making, some aspects of BDA research process such as big data collection, analysis, and interpretation are inherent. In order to capture these constituencies, search strings 'big data analytics*' combined with 'research method*', 'service systems*' 'research design*', and 'technique*' were established.

After determining suitable search strings, publications were identified using five databases including: Scopus (Elsevier), ScienceDirect (Elsevier), ABI/Inform Complete (ProQuest), Web of Science (Thomson Reuters), and Business Source Complete (EBSCOhost) to ensure that we capture all relevant scholarly journals and periodicals. However, both inclusion and exclusion criteria needed to be followed to make the search process stringent. As the first criterion, the search was narrowed down to the title, abstract, and keywords. The second criterion was to exclude disciplines that were not relevant to the study research area such as sociology, politics, physics, geology, or chemistry. A total of 2931 hits returned after searching in the above mentioned databases. After removing duplicates and applying selection criteria, 101 publications were downloaded and reviewed. However, only 14 publications were found relevant to the application of BDA-driven decision-making in service systems. Nonetheless, other related publications were also used in order to portrait a rich picture of the decision-making process. In this way, we are able to deliver more in-depth knowledge to the reader.

Drawing on the guidelines by Braun and Clarke (2006), we conducted a thematic analysis of the extant literature. The findings provide us six steps, which is consistent with T. H. Davenport and Kim (2013)'s six-step process in decision-making. We used Krippendorff's alpha (or, Kalpha) as a reliability measure to ensure further rigor in the thematic analysis (Krippendorff, 2004, 2007) following the guidelines of Hayes (2011) and De Swert (2012)to confirm the inter-rater reliability of the coded variables (Hayes & Krippendorff, 2007). To estimate the Kalpha, each of the subsamples of 14 articles were coded independently by two judges using a nominal scale ranging from 1 to 6 (i.e., 1= problem recognition, 2= review of past findings and context, 3= selection of variable and model development, 4= data collection, 5= data analysis and 6= actions on insights). The results provided us a Kalpha value of 0.84 which exceeds the cut off value of 0.80, and presents further validity in thematic analysis (De Swert, 2012). The next section discusses the findings of the review in detail.

As part of methods triangulation, the study conducted 30 semi-structured interviews to fuse the findings of thematic analysis from literature with interviews. Triangulating multiple sources of data can ensure the reliability of the study findings and reduce bias (Fusch, Fusch, & Ness, 2018). In other words, triangulation of multiple analysis methods significantly enhance the validity of the overall research process. In this case, qualitative methods enable to investigate in-depth how people place meanings on a certain phenomenon, process, structure, or setting (Silverman, 2011; Skinner, Tagg, & Holloway, 2000). Moreover, qualitative methods rely on people's own voices on how they perceive things and act under different conditions (Skinner, et al., 2000). This allows researchers to capture rich nuances of responses beyond surveys or experimental methods (Merriam & Tisdell, 2016; Silverman, 2011). A total of 30 interviews were conducted with BDA experts including professionals, researchers and academics. A demographic analysis of the respondents is presented in Appendix-2. On an average, each interview was conducted for 30-45 minutes. Interview data was analyzed using QSR NVivo 11 software (Bazeley & Jackson, 2013). For data analysis, thematic analysis technique was used as in the systematic review of literature. A deductive approach (Boyatzis, 1998) was followed in the thematic analysis as data were analyzed based on Davenport's (2013) six-step decision-making process.

4. Findings

Based on the findings of thematic analysis and qualitative interviews, this study presents six steps of BDA-driven decision-making process with relevant research agenda (see Appendix 1). Although the discussion is pivoted around the service systems, this process can be applied in any BDA context.

4.1. Step 1: Problem recognition

Recognizing the problem or the decision that needs to be taken is the initial step of the decision-making process. Correctly 'framing' – recognizing the problem and why it matters, is critical for the ensuing stages as well as what is expected to be accomplished at the end of the decisional process. The problem should be specific and focused in order to understand how it will be addressed and who will be involved (e.g., stakeholders) (T. H. Davenport & Kim, 2013). For instance, a participant mentioned a service company should be specific on which problem or what sort of innovation is expected to be addressed by BDA:

> *"We are gradually heading towards digital innovations, either through apps or* databased product, for example Amazon has come up with a recommendation system that transformed their business model which is based on big data analytics, ANZ bank has come up with property price prediction... [Therefore, the] question is what kind of service innovation are we looking forward to with the use of these analytics*?"(*Female, age 45-50).

Studies found through the systematic review provide cogent illustrations of the problem recognition step. As a matter of fact, Nielsen Holdings had competitive advantage over its competitors via collecting, storing, and processing data by their own. But, the whole business model had to be changed when cable/satellite companies started to sell consumer data; Nielsen no longer had a competitive advantage over data (Prescott, 2014). Nielsen had to define how to regain the company's competitive advantage as it was eroded due to new technological advances. Haier, first, pinpointed its problem in its online-to-offline (O2O) business model and then optimized its supply chain and resource allocation capabilities using vast amount of consumer data (Mishra, et al., 2017; Sun, Cegielski, & Li, 2015). F. T. C. Tan, Guo, Cahalane, and Cheng (2016) using a case study at Trustev - a global provider of digital verification technology, discussed how problems related to identity fraud in e-commerce was combatted using BDA. Miah, et al. (2017) investigated how firms can use social media data for tourism destination management. A specific problem they addressed was how BDA and social media can be used to forecast future and seasonal tourism demands.

These findings provide support for problem definition as the first step in the decision process to identify a specific business problem or, components of a problem. T. H. Davenport and Kim (2013) stressed the importance of this step is to clearly frame the problem, and they caution that high volumes of data or sophisticated analytics will not help unless business problem is correctly identified. Lilien and Rangaswamy (2006) claimed that when the problem drives the choice of models, it elevates the effectiveness of the models, quality of the insights generated, and the consistency of decisions that are taken based on these models. Our findings suggest that problem recognition is the first critical step in data driven decision-making, which is highlighted by one participant in telecommunication service system as follows:

> *"As I mentioned before that big data was once only* technology-driven but now it has to be business problem-driven. Our company was focusing on technology in the past but *now it has changed its focus to solving business problems with big data".* (Male, age 41-45)

4.2. Step 2: Review of previous findings and context

Framing the problem not only requires to identify the problem but also necessitates exploring relevant past findings and context (T. H. Davenport, 2013; Salehan & Kim, 2016). It is vital that organizations and researchers grasp previous findings to learn existing measures and avoid pitfalls. Reviewing can often lead to substantial revision of the problem and contextual exploration (e.g., resources & constraints, economic and legal environment, past findings and forecasts etc.) which will result in better framing of the problem (T. H. Davenport & Kim, 2013). According to one participant,

> *"In one case study we are using prediction to know what we can* do to up sell or cross-sell our product and services, the only way we can do is by reviewing previous findings and context regarding a consumer, hence, by we *can predict what customer's next* action might be and make sure the customer to not turn away*"*. (Male, age 41-45)

C. K. H. Lee (2017) investigated how anticipatory delivery can be enhanced in omni-channel commerce. For this purpose, the author reviewed several previous methods, including Amazon's anticipatory shipping model which is used to predict a consumer's purchase decision and begins shipping the product before the order is placed. Miah, et al. (2017) found that previous analytical efforts have been taken to automatically detect tourist behavior and preferences. These authors realized the necessity for visual photo content and metadata processing to identify tourist preferences and experiences. Salehan and Kim (2016) identified existing methods to predict consumer review's performance based on numeric star rating and word count, and they identified the importance of extracting the sentiment of both title and the text using BDA techniques. It has become a strategy to collaborate or integrate with other companies who are better in BDA to learn and support their efforts. For example, in gaining competitive advantage in the market, Nielsen Holdings identified the importance of BDA, which its competitors such as Rentrak and TRA were using for robust data processing. Nielsen acquired Audience Analytics Technology Inc. that enabled them to process, integrate, and analyze mass volume of consumer data that resulted Nielsen to gain more information about their consumers and competitors (Prescott, 2014). Similarly, Haier lacked big data usage experience and by collaborating with Alibaba, and improved their abilities to identify and address their issues in e-commerce capabilities (Sun, et al., 2015). Overall, close investigation of previous findings and context can lead to revision and/or proper framing of the problem, and avoid replication and pitfalls.

4.3. Step 3: Select the variables and develop the model

A model is a simplified representation of a particular problem. Modeling and formulating hypotheses about the relationship between different variables and their impact on the outcome is critical to solve a problem (T. H. Davenport & Kim, 2013). Even though it is useful to think expansively in the problem identification phase, by the end of this step, it is required to have a precise problem statement and a model consisting study variables. While big data with its unprecedented volume, variety, and variability (Akter & Wamba, 2016) provides opportunities for deeper insights and better decisions, it might require complex modeling which can be a challenge (Sivarajah, et al., 2017). Traditional statistical and econometric models are incapable of handling mass volume and variety of data and therefore complex models that can handle big data and its different effects (i.e. direct and indirect) are required (Wedel & Kannan, 2016).

C. K. H. Lee (2017) developed a predictive model including variables such as transportation cost, travelling time to determine the allocation of products to different distribution centers in order to optimize anticipatory delivery times. Xiang, Schwartz, Gerdes, and Uysal (2015) developed a model to estimate the relationship between guest experience and satisfaction in the hospitality industry using online consumer reviews. Chiang and Yang (2017) proposed a model using personality traits based on country-of-origin and brand personality to predict potential customer lifetime value. In summary, by the modeling stage, decision makers would need to have a narrow focus of the problem sought and an understanding of what variables need to be included and what relationships to be measured. One participant highlighted the importance of identifying proper determinants to address the problem in the modeling phase, as followed:

> "My suggestion would be to focus on how they can create value, and model the predictor of that and investigate how well they understand the drivers of that outcome, *so it's a tool to understand your product ,customer and the market against actual data,* you may think that X drives our performance, well what data do you have to support that, and once you start modeling your outcome of interest against your hypothesis drivers then that gives you an understating of how well you understand your operations, *and that might prompt rethinking of strategies to improve performance."* (Male, age 51-55)

4.4. Step 4: Collect the data

The next step of solving the problem is to collect all relevant data to measure and test the model (T. H. Davenport, 2013; Janssen, et al., 2017). Today, large volumes of data emanating from different sources such as transaction, click stream, and video data are available for companies. They come mainly in three different forms: structured, semi-structured, and unstructured (Gandomi & Haider, 2015). Structured data can originate from sources such as internal reporting systems, operational systems (e.g., transaction data) and automated systems (e.g., machine data) and can be relatively captured, organized, and queried easily (Phillips-Wren, Iyer, Kulkarni, & Ariyachandra, 2015). Structured data consist of four main dimensions: variables, attributes, subjects, and time (Naik, et al., 2008). Semi-structured data, which lack fixed structure but still with identifiable features are becoming a popular data source in BDA (Phillips-Wren, et al., 2015). Unstructured data (e.g., blogs, wikis, and images) are usually ill-defined and variable, but currently have a great demand in BDA.

Despite the overabundance of data sources and data formats, it will not help better decisions unless decision makers identify data sources that are strategically important to the problem addressed (Phillips-Wren, et al., 2015). The ultimate aim of collecting mass volumes of data is to be utilized in decision-making and create value, but only 0.5 percent of collected data have been claimed to be analyzed (Bumblauskas, et al., 2017). Dearth of data provenance and lack of understanding about the immanent scales in data collection and processing can hinder deriving actionable insight from data (C. P. Chen & Zhang, 2014; Sivarajah, et al., 2017). According to one participant, these challenges are more pertinent to smaller companies. He indicated:

> *"I have seen larger companies team up with software providers like IBM and Microsoft,* but smaller companies are really struggling with it, as data comes from different *sources small companies have so much data and workloads that they don't have time and resources… they need to* be prepared well enough." (Male, age 36-40)

Companies use primary data sources such as company transactions, behavioral, and historical data for analytical purposes (Chiang & Yang, 2017; F. T. C. Tan, et al., 2016). With technological advancements, developments such as cloud storage and social media have increased access to a colossal amount of publicly accessible secondary data. Nielsen was primarily based on their primary data sources. However, when diverse consumer data were available for purchasing in the market, Nielsen could no longer rely on their own data generation (Prescott, 2014). C. K. H. Lee (2017) collected data from different channels such as physical, catalogue, mobile, and online channels to optimize anticipatory shipping time. Miah, et al. (2017) used publicly available data on the photo-sharing site Flickr for improving strategic decision-making on tourist destination management. He, Wang, and Akula (2017) explained how companies could capitalize Twitter data of their competitors to facilitate strategic planning and competitive positioning. Similarly, Guo, Sharma, Yin, Lu, and Rong (2017) used free online content to develop cost-efficient methods using BDA to monitor a firm's market position in real time. Therefore, organizations need to decide what data sources are strategically useful to them and how relevant are the data to the problem and model. According to a participant, type of data collection might vary across the industry:

> *"Depending on the industry, for example telecommunication industry use sentiment analytics like how users respond to advertising campaign, product and services, forecasting about future direction. In banking sector like they use of lot of analytics for personal profiling like proving specific credit cards offers, identifying customers not paying debt on debit card.. [Requirement of data] can be varying depending on different industries." (Male*, age 36-40)

4.5. Step 5: Analyze the Data

It is important to have proper tools and approaches to effectively exploit big data (Al Nuaimi, Al Neyadi, Mohamed, & Al-Jaroodi, 2015). Advanced analytical methods have improved the insights that can be gained and decisions that can be taken from big data. Analytical methods facilitate to find relationships between variables that are embedded in data (T. H. Davenport & Kim, 2013) and this can span to different activities including different stages (Phillips-Wren, et al., 2015). Within the overall analysis process, initially data mining and cleansing are conducted. This refers to extracting and cleaning data that can be diverse, vibrant, divergent, and interrelated (J. Chen, et al., 2013). This is followed by aggregation and integration of data which are amorphous and can have myriad meanings and lack natural binding (Sivarajah, et al., 2017). Then, data analysis is performed using appropriate BDA techniques. From a taxonomical standpoint, most scholars clarify BDA techniques under three categories: descriptive, predictive and prescriptive (Delen & Demirkan, 2013; Wang, Gunasekaran, Ngai, & Papadopoulos, 2016). Nevertheless, some scholars identify other categories such as inquisitive, pre-emptive analytics, and diagnostic analytics (e.g., Sivarajah, et al., 2017; Wedel & Kannan, 2016).

Descriptive analytics comprise of tools and statistics to describe and define the current state of a problem – 'what happened?' or 'what is happening?' They are useful to produce standards and periodic business reports, ad-hoc or on-demand reports, and dynamic reports and can provide insights into novel problems and opportunities (Delen & Demirkan, 2013). Predictive analytics are concerned with predicting or forecasting (e.g. trends and associations) based on inherent relationships among variables (Waller & Fawcett, 2013). These techniques generally answer 'what will happen?' or 'why something happens?' and are useful to ascertain future prospects and possibilities and to why something can happen (Delen & Demirkan, 2013). Prescriptive analytics have become crucial for data-driven decision-making as these analytical techniques enable to find optimal course of action or a decision given multiple alternatives under different requirements and constraints (Phillips-Wren, et al., 2015). Prescriptive modeling also delivers rich information and expert opinions (Watson, 2014) and the optimization and randomized testing can deliver positive outcomes such as service enhancement and cost reduction (Joseph & Johnson, 2013). Apart from these analytical categories, Sivarajah, et al. (2017) identify inquisitive analytics – analyses that can be used to accept or reject business propositions, and pre-emptive analytics – analyses that can enable to take precautionary actions against undesirable influences. Moreover, diagnostic analytics are useful for hypothesis testing and estimate relationships between variables (Wedel & Kannan, 2016). However, these categories are more or less variations of the descriptive, predictive, and prescriptive analytical methods. Several of these BDA techniques can be important to the service industry. According to a participant:

> *"The service* industry has large quantities of customers and they provide certain services, and their performance is determined by the satisfaction from the customers, they want to use big data for prediction to find out customer demand and emotions of customer about th*e product…* I believe data visualization tools are important at this moment, with data you can generate charts and graphs which can be used to show the outcome of the data, nowadays deep learning and neuron networks are very popular, they can do a lot of analysis on that and get different results, like clustering, forecasting, prediction and trying to find future within the data, so at the end visualization is very *important."* (Male, age 50-55)

Literature review also highlights several examples of BDA use, related to the service industry. Miah, et al. (2017) analyzed Flickr data using text processing, geographical data clustering, visual content processing and time series modelling to make decisions on tourist destination management. C. K. H. Lee (2017) used predictive and anticipatory analytics through a combination of GA and cluster-based association rule mining to optimize anticipatory shipping. Guo, et al. (2017) combined several techniques including Topic Modeling, MDS, K-Nearest Neighbors (k-NN) Clustering with data visualization using free online content for automated competitor analysis. He, et al. (2017) used text mining, sentiment analysis and comparative analytics to analyze social media data for competitor analysis. The use of several other analytic techniques such as sentiment analysis (Phillips-Wren & Hoskisson, 2015), algorithm analysis and machine-learning (C. K. H. Lee, 2017; F. T. C. Tan, et al., 2016), and regression analysis (Loukis, Pazalos, & Salagara, 2012) can be found in the literature. Overall, there are several analytical methods available for big data analysis. However, it is important that organizations identify relevant methods that suit the problem at hand, and develop human resources that can perform that advanced analytics. According to a participant, use of BDA can vary according to different service sectors based on the problems or goals they have:

> *"*Depending on the industry, for example telecommunication industry uses sentiment analytics like how users respond to advertising campaign, product and services, forecasting about future direction. In banking sector like they use lot of analytics for personal profiling like providing specific credit cards offers and identifying customers not paying debt on debit card... [use of BDA can] be vary depending on different industries.*" (Male, age 3*6-40)

4.6. Step 6: Actions on insights

The final step involves taking actions on the problem based on the insights gained from big data. After analyzing the data, a comprehensive interpretation is required to gain valid insights. Interpretation is a way of visualizing data that can make data understandable in order to extract sense and knowledge (Kokina, Pachamanova, & Corbett, 2017). According to Zhong, et al. (2016), a key purpose of BDA is to uncover implicit information and knowledge from big data to support good decision-making. In general, the basic aspects of a 'good' decision are the quality of the decision and the acceptance of the decision. To gain acceptance of any BDA-driven decision communication is key (Sutanto, Kankanhalli, Tay, Raman, & Tan, 2008). This include communicating or telling a story from the results in a way that can be understood by all stakeholders (Sharma, et al., 2014). Telling a story is how numbers talk to people and it is a convincing way to communicate to non-analytical people (T. H. Davenport & Kim, 2013). Even all the previous steps are performed with precision, a better outcome cannot be expected unless decision makers do not act on the derived knowledge and insights. As mentioned by one participant:

> *"I don't think analytics capabilities are* an issue here as those capabilities are available in third-party services. So an organization does*n't need* in-house capabilities, but what it needs is a culture of decision-making based on data. In most organizations decision-making resource allocation is either based on the convention on how things will happen here or based on some political negotiation and so on. Data rarely enters the picture in decision-making in most of the organizations and analysis of data is even rare. So it is not about analytics capability but a culture of data-driven decision-making which is more important... what is missing is the managers who rely on data to take their decisions and that goes back to the culture of decision-making where the data and analysis play a small role in decision-making.*" (Male, age 5*1-55)

Several steps in the BDA-driven decision-making process involve technology and technicality. However, these steps, including analysis and interpretation, require human intervention to generate actionable insights (Jagadish, et al., 2014). Application of advanced BDA will not automatically generate insights, rather "insights emerge out of an active process of engagement between analysts and business managers using the data and analytic tools to uncover new knowledge" (Sharma, et al., 2014, p. 435).

Prescott (2014) explained how Nielsen was able to gain incisive insights on consumer behavior by measuring and analyzing brainwave activity, eye-tracking, and electrical conductance of the skin when exposed to an advertisement, and thereby deliver powerful and targeted advertising. Miah et al.'s (2017) application of BDA into the analysis of geo-tagged and representative photos provided numerous insights into tourist perceptions and behaviors. Based on these insights, one action authors have recommended was that destination management organizations should develop different travel packages that cater for the demands of local and inter-state markets. Singh, Irani, Rana, Dwivedi, Saumya, and Roy (2017) have developed models based on machine learning which help predicting the helpfulness of consumer reviews using textual features such as polarity, subjectivity or reading ease. Chiang and Yang (2017) used BDA to understand the relationship between consumer traits and brand personality of beer brands. The authors found consumers are likely to purchase brands with traits similar to their own personality traits. Saboo, Kumar, and Park (2016) identified that companies can increase their revenue by more than 17% by reallocating their marketing resources based on the time-varying effects model. These examples provide clear interpretations of BDA in which decision-makers can act on insights. Participants shared similar ideas. According to a participant:

> "Data can be turned into information, information can be turned into knowledge and knowledge can be turned into wisdom, in order to understand the past or understand what is coming next in terms of event, or predict the future through economic mechanism, basically it is the analysis of behavior, through human or non-living things and being able to understand events better, sometimes before they happen or on reflection looking back after that happens. *So that what big data is to me it's the* assemblage of structured and unstructured data generated by both paper based and digital means for understanding and sometimes perhaps for the optimization of *processing a particular industry." (Female, age* 40-45)

5. Discussion

The proposed six-step framework provides a clear and useful guide to employ BDA in decision-making. However, even if the step-wise process is sequential and linear, each step can improve other steps; therefore, decision-makers can always take a step back to build upon new knowledge. For instance, in the analysis stage, analysts might decide to collect more data to derive more knowledge, or analysis can even transpire newer problems that can result in the revision of the whole model. Under these circumstances, BDA-driven decision-making is considered to be vastly different from more structured traditional decision-making (Elgendy & Elragal, 2016). Despite the simplicity of the framework, BDA-driven decision-making is not without challenges (Bumblauskas, et al., 2017; Sharma, et al., 2014). In the BDA context, previous studies have identified challenges related to the big data sources and big data itself, data processing, and management (Janssen, et al., 2017; Sivarajah, et al., 2017; Zicari, 2014). These challenges are decisive in how firms embrace BDA in their decisions. Jagadish, et al. (2014) claimed that deriving value from BDA is a multi-step process that runs from data acquisition to interpretation and deployment, and focusing on few steps can cost the whole purpose of value creation.

Davenport (2013) and Davenport and Kim (2013) elaborated the six-step process under three analytical thinking stages. The first two stages – problem recognition and review of previous findings from the 'problem framing' stage. The next three steps – modeling, data collection, and data analysis constitute the 'solving the problem' stage. The last step – acting on insights represents the 'communicating and acting on results' stage. The problem identification or framing stage is prevalent in decision-making and design science process models. For instance, first phase of the Simon's (1977) decision-making model – intelligence or 'deciding what to decide', focused on identifying and formulating the problem and the context and conditions surrounding it. Similarly, in design process models, for instance, Peffers, Tuunanen, Rothenberger, and Chatterjee (2007) have distinguished 'problem identification and motivation' to be the initial choice as defining the problem is vital to atomize the problem and provide solutions. These decision-making models and theories can extensively guide decision processes that aim to integrate BDA.

After a problem has been properly framed, solutions have to be identified based on modeling, data collection and analyses using suitable techniques. Several challenges inherent in big data impede the integration of BDA. Some challenges such as heterogeneity, inconsistency, incompleteness, abundance, trustworthiness, and rapidity of big data are as important as the benefits big data can deliver (J. Chen, et al., 2013; Gandomi & Haider, 2015; Jagadish, et al., 2014). For instance, overcoming data binge or overload of data (Bumblauskas, et al., 2017) and poor data quality (Hazen, Boone, Ezell, & Jones-Farmer, 2014) have taken increased attention of scholars and practitioners. These involutions are exacerbated by the data processing and infrastructure challenges. The voluminous, variety, and velocity of big data combined with data provenance, and deficiency of knowledge in scales immanent to data collection have created concerns over data acquisition, warehousing, and processing (Paris, Donnal, & Leeb, 2014). Several challenges due to unstructured, vibrant, diverse, and unreliable attributes of big data have proven to be challenging in data mining, cleansing, integration, and analysis (J. Chen, et al., 2013; Kaisler, et al., 2013; Karacapilidis, Tzagarakis, & Christodoulou, 2013). Apart from technological resources, it is essential that organizations have the human resources or the talent pool required to run this process (Dubey & Gunasekaran, 2015; Kiron, Prentice, & Ferguson, 2014). In addition, BDA process involves the collaboration of different people with different skills-set, departments, and stakeholders (Janssen & Kuk, 2016). Therefore, apart from the technological focus, organizations need to be aware about the human aspect of proper BDA integration to the decision-making process.

Theoretical Contributions

Big data in service systems can only lead to competitive advantage if organizations use appropriate management, talent and technology resources (Manyika, et al., 2011). For instance, organizations need to decide what data sources, platforms, or human resources are strategically important to them (Phillips-Wren, et al., 2015). In this context, researchers can be greatly benefited by extending management theories, such as the resource-based view theory (RBV; Barney, 1991), knowledge-based view theory (KBV; Grant, 1996), and dynamic capability theory (DC; Helfat & Peteraf, 2009). For instance, RBV postulates that an organization's knowledge resources are unique and it provides the ability to renew or reconfigure its existing resource base that can create positive organizational outcomes (Wu, 2006). Similarly, dynamic capabilities are important for organizations to modify their resource base to adapt to changing environmental conditions that can lead to sustaining the organization's competitive advantage over time (Teece, Pisano, & Shuen, 1997). Therefore, firms need to consider how BDA can enhance knowledge and dynamic capabilities of the firm that can result in positive outcomes including competitive advantage. For instance, Côrte-Real, et al. (2017) provided empirical evidence how BDA can impact organizational agility via knowledge management that can lead to process performance and competitive advantage. The adoption of BDA at the decision-making process can be considered an organization-wide transformative process because it requires the interaction of different teams, departments, and stakeholders. Communication models used in continuous organizational change can greatly facilitate to understand this transformative process. For instance, dialogic change communication that suggests a constructive and relational dialogue is considered more suitable for continually changing contexts (Eisenberg, Andrews, Murphy, & Laine-Timmerman, 1999; Weick & Quinn, 1999). Further communication theories can help decision-makers to communicate actionable knowledge and insights generated from BDA effectively. Similarly, other managerial issues such as privacy, security and infrastructure issues in BDA can be further explored using theories such as IT quality theory (Nelson, Todd, & Wixom, 2005), IS success theory (DeLone & McLean, 1992), and justice theory (Culnan & Bies, 2003). de Camargo Fiorini, Roman Pais Seles, Chiappetta Jabbour, Barberio Mariano, and de Sousa Jabbour (2018) report that big data analytics can also be explored by applying, for instance, actor network theory, agency theory, contingency theory, diffusion of innovation theory, game theory, ecological modernization theory, institutional theory, knowledge management theory, social capital theory, social exchange theory, stakeholder theory, transaction cost theory.

Practical Contributions

The final stage of the proposed decision-making framework emphasizes on actions by practitioners on insights, which generally involves communication of BDA-based results to a general audience. The initial phases of the proposed framework involve data collection and analysis of big data, which are mostly conducted by data miners and analysts. However, practitioners can play a huge role in implementing the final step. McAfee, et al. (2012) and Falletta (2014) argue that practitioners cannot depend purely on intuitive and experienced-based decision-making anymore. Especially, practitioners are predisposed to ignore data-driven findings and insights when it threatens existing beliefs and practices (Rasmussen & Ulrich, 2015). Therefore, practitioners in the first place must be reactive to embrace insights from BDA and communicate them effectively. As contended by Akter, et al. (2019) “the lack of organizational ability to articulate a solid and compelling business case is likely to be an overarching challenge for BDA” (p. 190). Other BDA managerial challenges including privacy and data ownership (Jagadish, et al., 2014; Martin, 2015), security (Xu, Jiang, Wang, Yuan, & Ren, 2014), data governance (Hashem, et al., 2015; Otto, 2011) and operational expenditures (Vidgen, Shaw, & Grant, 2017) continue to challenge data driven decision making (Fosso Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015).

Limitations and Future Research Directions

The current paper focuses on big data analytics-driven decision making within service systems. The paper is based on a systematic literature review and traiangulation of the findings of thematic analysis and in-depth interviews, however, it is limited towards understanding the six-step framework in analytics-driven decision making only. Additional studies are required to develop a full picture of analytics-driven decision making. Furthermore, this paper is limited to addressing factors influencing the decision making only. The broader perspective of big data and its complex relationship with a specific service system are not the focus of this paper. Since service system is a contextual phenomenon; impact of cultural and social influence on how individuals interact with it can vary. Therefore, studies should take into account the dynamism of a specific service system while generalizing our findings to other contexts. Future research, therefore, can focus on analytics-driven decision making in the contexts of various service systems, such as supply chain, auditing, healthcare, digital marketing etc. With regard to research methods, the most common form of method triangulation is using both qualitative and quantitative methods, however, our study relied on two qualitative methods (i.e., thematic analysis+interview findings) to support the results. As such, this creates an opportunity for future research to conduct further methodological triangulation (e.g., interviews and survey) to support findings.

Overall, based on Bumblauskas, et al. (2017, p. 708), we argue that “data with no objective analysis, and knowledge without action, have relatively marginal value to organizations” (p. 9). Therefore, first, decision-makers need to be aware of how data can be converted into actionable knowledge and how to effectively communicate and act on that knowledge. Davenport and Prusak’s (1998) distinction between data, information, and knowledge, and Argyris’s (1995) conceptualization of actionable knowledge are useful theses for both future research and practice. We believe that the six-step process discussed in this paper is a useful guide for organizations to adopt BDA-driven decision-making. As indicated in Appendix 1, we have outlined various research questions that can be inquired as research agenda when dealing with each step.

6. Conclusions

BDA has become increasingly popular more than any other managerial paradigms (Delen & Demirkan, 2013; Kitchens, Dobolyi, Li, & Abbasi, 2018) due to its ability to generate valuable knowledge and actionable insights (Côrte-Real, et al., 2017). Nevertheless, the use of BDA for effective and quality decision-making has become a challenge for many companies (Kowalczyk & Buxmann, 2015; Zhu, Song, Hazen, Lee, & Cegielski, 2018). In order to overcome this challenge in theory and practice, we provide a six-step decision-making process on how to properly execute BDA projects to support data-driven decision-making. This process provides a basis for scholarly research to build upon and delivers practitioners with a step-wise guide for integrating BDA to make better decisions. Through this systematic review, this study has also provided empirical evidence from service organizations to establish the workability of this process.

Appendix 1: Research Questions and Sources of Literature to Support Big Data Analytics Decision-making Process.

Steps in BDA research process	**Research agenda/Research Questions**	**Source**
Step 1: Problem recognition	What is the management decision problem and respective big data research problem? How to refine and develop the management decision problem through discussion with decision-makers and big data experts?	Batarseh and Latif (2016); Chiang and Yang (2017); Guo, et al. (2017); He, et al. (2017); C. K. H. Lee (2017); Loukis, et al. (2012); Miah, et al. (2017); Phillips-Wren and Hoskisson (2015); Prescott (2014); Saboo, et al. (2016); Salehan and Kim (2016); Sun, et al. (2015); F. T. C. Tan, et al. (2016); (Dubey, et al., 2018); Xiang, et al. (2015)
Step 2: Review previous findings and context	What is the environmental context of the problem (e.g., past findings & forecasts, PESTL factors, resources and constraints, objectives etc.) and relevant big data analytics?	Batarseh and Latif (2016); Guo, et al. (2017); C. K. H. Lee (2017); Miah, et al. (2017); Phillips-Wren and Hoskisson (2015); Prescott (2014); Salehan and Kim (2016); Sun, et al. (2015); F. T. C. Tan, et al. (2016); Papadopoulos, et al. (2017)
Step 3: Approach to the problem by selecting variables and formulating a model.	What is the theory behind the big data driven analytical model? What are the specific components of the business problem? What variables should be taken into account to develop the BDA model?	Batarseh and Latif (2016); Chiang and Yang (2017); Guo, et al. (2017); He, et al. (2017); C. K. H. Lee (2017); Loukis, et al. (2012); Miah, et al. (2017); Phillips-Wren and Hoskisson (2015); Saboo, et al. (2016); Salehan and Kim (2016); Sun, et al. (2015); F. T. C. Tan, et al. (2016); Xiang, et al. (2015)
Step 4: Collect the data	What factors influence data cost, quality, retention, visualization, governance, security, and privacy?	Batarseh and Latif (2016); Chiang and Yang (2017); Guo, et al. (2017); He, et al. (2017); C. K. H. Lee (2017); Loukis, et al. (2012); Miah, et al. (2017); Prescott (2014); Phillips-Wren and Hoskisson (2015); Saboo, et al. (2016);

	What types of data are more suitable to address the research problem at hand (e.g., structured, unstructured, or both)?	Salehan and Kim (2016); Sun, et al. (2015); F. T. C. Tan, et al. (2016); Xiang, et al. (2015)
Step 5: Analyze the data	What type of BDA model (e.g., descriptive, predictive or prescriptive analytical) can best answer the research question? How can integration of analytical techniques and human sense making improve the generation of actionable insights?	Batarseh and Latif (2016); Chiang and Yang (2017); Guo, et al. (2017); He, et al. (2017); C. K. H. Lee (2017); Loukis, et al. (2012); (Cao, Duan, & El Banna, 2019); Miah, et al. (2017); Phillips-Wren and Hoskisson (2015); Saboo, et al. (2016); Salehan and Kim (2016); F. T. C. Tan, et al. (2016); Xiang, et al. (2015)
Step 6: Act on Insights	How to leverage BDA insights to create transactional, strategic or transformational business value? How will immediacy and requirement for real-time decision-making influence previous steps of the process? What is the effect of existing organizational structures, decision-making processes and culture on BDA-driven decision-making? How can organizations employ BDA to improve the acceptance of decisions?	Batarseh and Latif (2016); Chiang and Yang (2017); Guo, et al. (2017); He, et al. (2017); C. K. H. Lee (2017); Loukis, et al. (2012); Miah, et al. (2017); Phillips-Wren and Hoskisson (2015); Prescott (2014); Saboo, et al. (2016); Salehan and Kim (2016); Sun, et al. (2015); F. T. C. Tan, et al. (2016); Xiang, et al. (2015)

Appendix 2: Demographic Analysis of the respondents

Demographic Characteristic	**Sub-Level**	**Count n=30**	**(%)**
Gender	Male	28	94
	Female	2	6
Profession	Relationship Manager	2	
	Senior Vice President	1	
	Professor	8	
	Deputy Chief Executive	1	
	Director, New Business	1	
	Customer Delivery Manager	1	
	Head of Data and Info Management	2	
	Vice President – Govt & Healthcare	1	
	Business Analyst	3	
	Services Manager	1	
	Purchase Officer	1	
	OSS Domain Lead	1	
	Branch Manager	1	
	Information Architect	1	
	Business Banking Manager	1	
	Research	3	
	Retail	1	
Education	Undergraduate	10	34
	Postgraduate	12	40
	PhD	8	26
Age	26-35	6	20
	36-45	10	34
	46-55	11	37
	>55	3	9

Appendix 3: Research process of the study

	Stage	Review Phase	Activities
Planning the review	**1**	Identification of the need for the review	• Development of a cross-disciplinary, international panel consisting of theory and methods experts in management, operations, marketing and IS.
	2	Development of the review protocol	• The study highlighted the research problem and its significance focusing on the research question “What are the steps in the BDA-driven decision-making process in service systems?”
Conducting the review and triangulation	**3**	Identification of research	• A systematic review of the literature on big data analytics and service systems using Scopus (Elsevier), ScienceDirect (Elsevier), ABI/Inform Complete (ProQuest), Web of Science (Thomson Reuters), and Business Source Complete (EBSCOhost).
	4	Selection of studies	• Search strings: ‘big data analytics*’ combined with ‘research method*’, ‘service systems*’ ‘research design*’, and ‘technique*’. • Inclusion criteria: title, keywords and abstract • Exclusion criteria: disciplines such as sociology, politics, physics, geology, or chemistry.
	5	Study quality assessment	• Thematic analysis of the literature identified 6 themes with a Kalpha value of 0.84
	6	Triangulation	• The study triangulated the findings of thematic analysis and qualitative interviews.
Reporting	**7**	Recommendations	• The study presented a six-step decision-making framework for service systems in the context of big data environment.

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