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BIG DATA ANALYTICS AND FIRM INNOVATIVENESS: THE MODERATING EFFECT OF DATA-DRIVEN CULTURE

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Abstract

In recent years, big data analytics (BDA) have become an important subject for both researchers and business professionals. Especially, today's managers and researchers put great emphasis on big data as a new source of innovation and competitive advantage. In the literature although there were some studies that examined BDA capability and firm performance relation, any studies have been conducted to directly investigate the effect of BDA capability on firm innovativeness. In this context we proposed a research model to investigate the effect of BDA capability on firm innovativeness moderated by the effect of data-driven culture. We created BDA capability dimensions as technical capability, managerial capability and talent capability depending on the previous studies in this field. Also we treated data-driven culture as moderator because without the acceptance and readiness of the whole organization for big data transformation, big data initiatives cannot be successful. With this model we created a roadmap for the following researchers to empirically test the expectations of managers and academicians. Therefore following researchers can fill the gap in the literature by showing how firm innovativeness will be affected by BDA capabilities.

Keywords: Big Data, big data analytics capability, firm innovativeness.

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1. Introduction

In recent years, big data has become a major interest for companies and researchers. With the development of technology, a continuous data flow has emerged from different channels such as web sites, forums, social media applications, mobile phones and so on. The information stored in these data flows has a great importance for companies to make accurate strategies about their business fields and to take quick and correct decisions. That's why companies utilizing from big data analytics perform better than their rivals and create a sustainable competitive advantage.

Some researchers have used different expressions for BDA such as "management revolution" (McAfee & Brynjolfsson, 2012, p.4), "the next frontier for innovation, competition and productivity" (Manyika et al., 2011, p.1), "the next blue ocean in nurturing business opportunities" (Kwon et al., 2014, p.387), and "the potential to revolutionize the art of management" (Wamba et al., 2015, p.234). In general, according to one of the most known definition, BDA is defined as "the collection of data and technology that accesses, integrates, and reports all available data by filtering, correlating, and reporting insights not attainable with past data technologies" (APICS, 2012).

BDA has become important for companies especially in decision making processes (Hagel, 2015). In addition to being an important distinction between high-performance organizations and low-performance organizations, BDA have made companies more proactive and visionary, reduced customer acquisition costs and contributed to firm revenue growth (Liu, 2014). Companies use BDA to study whole organizations, teams and workgroups to understand individual or group behaviors, social dynamics, coordination challenges and performance outcomes. On the customer side, they use BDA to get insights about purchasing intentions, consumption habits, communication channels, distribution channels, advertising, pricing, new product success and so on (Xu & Frankwick, 2016; George et al., 2014).

In the literature it is seen that firms need to develop BDA capabilities in order to be successful in big data investments. Ross et al. (2013) state that many companies fail in big data investments because these firms are not capable in making decisions on the basis of information that is filtered out of big data. Because these firms do not have required BDA capabilities to manage and utilize from big data. Depending on IT basis, researchers have created different BDA capabilities to utilize data sets in coordination with IT assets and human talents to gain sustainable competitive advantage (Garmaki, Boughzala & Wamba, 2016). From this perspective, in many studies researchers investigated the effect of BDA capability on firm performance (e.g. Gupta & George, 2016; Akter et al., 2016; Wamba et al., 2017).

In this study, with the role of BDA capability, we investigate the effect of BDA on firm innovativeness under the moderation of data-driven culture. In previous studies, although researchers emphasized big data as a driver for innovation and competitive advantage (Tan et al., 2015; Manyika et al., 2011; Erevelles et al., 2007) there were not any satisfactory empirical study to show the direct effect of BDA on firm innovativeness. With our research model and developed propositions we have created a road map for future studies.

This paper is organized as follows: the next section gives theoretical information about big data, BDA and BDA capabilities. The following section focuses on research model and proposition development. In the last section, expected results, research contributions and limitations are given.

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2. Theoretical Framework

2.1. Big Data Definition

McAfee and Brynjolfsson (2012) point out that there are 3 main differences that distinguish big data from other data: volume, velocity and variety. Oracle (2012) added value dimension to these three dimensions and White (2012) added fifth dimension, veracity, and argued that big data has five distinguishing dimension: volume, velocity, variety, value and veracity.

Volume: The most distinguishing dimension of big data. It is used for to state that huge amount of data are collected from various resources. (O'Leary, 2013).
Velocity: It refers to the speed of collection and transmission of data (Russom, 2011). The data collected at high speed can be analyzed in real time, near real time, or in batches (Demchenko et al., 2013).
Variety: It points out heterogeneity of data types (Kaur & Sood, 2017). Big data can be collected from different resources and can be in different formats but in any relevant analysis common results can be derived using data from these different sources (Russom, 2011; O'Leary, 2013).
Value: It refers to the process of knowledge generation that creates value for companies (Kaur & Sood, 2017). Too much data is not enough alone. The important thing is to analyze data that creates value for companies to generate new knowledge from the hidden information in big data sets.
Veracity: It is related to reliability, consistency, accessibility and transparency of big data. In this context, providing data security becomes important in the process of obtaining, storing and analyzing the data (Demchenko et al., 2013).

Big data literature showed that big data is not only related to huge data volumes, it is also related to diversity of data types and delivery speed. The source of this huge amount of data can be internal or external and the structure of data can be structured or unstructured (Russom, 2011; Raguseo, 2018). In the literature there are many big data definitions. To understand big data more clearly some of the definitions are given in the table below.

Table 01. Big Data Definitions

Resource	Definition
Kaur and Sood, (2017, p.1)	"A collection of huge volumes of diverse types of structured and unstructured data that cannot be handled by state-of-the-art data processing platforms"
Dumbill, (2013, p.1)	"data that exceeds the processing capacity of conventional database systems. The data is too big, moves too fast, or doesn't fit the structures of your database architectures. To gain value from this data, you must choose an alternative way to process it"
Bayer and Laney, (2012)	"High volume, velocity and variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision-making"
Havens et al., (2012, p.1130)	"data that you cannot load into your computer's working memory"
Manyika et al., (2011, p.1)	"datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyse"

Microsoft, (2013)	"The process of applying serious computing power, the latest in machine learning and artificial intelligence, to seriously massive and often highly complex sets of information "
Boyd and Crawford, (2012, p.663)	"cultural, technological, and scholarly phenomenon that rests on the interplay of technology, analysis and mythology"
Fisher et al., (2012, p.53)	"Data that cannot be handled and processed in a straightforward manner"
Intel, 2012	"Complex, unstructured or large amounts of data"
Morabito, (2015, p.viii)	"dubbed to indicate the challenges associated with the emergence of data sets whose size and complexity require companies to adopt new tools and models for the management of information"
De Mauro et al., (2016, p.131)	"a is the Information asset characterised by such a High Volume, Velocity and Variety to require specific Technology and Analytical Methods for its transformation into Value"

2.2. BDA and BDA Capabilities

BDA is a term briefly used to describe advanced analysis techniques applied to big data. (Russom, 2011, p.8). When considering today's technological advances and people's dependence on the technology, as a result of our daily life we leave behind detailed digital records. Our twitter shares, social relationships, shopping habits, searches through web sites, photographs and videos, and even our physical movements and even the roots of cars create important usable digital records. For sciences that study human behavior this data pool has an irresistible appeal. Therefore private sector and public sector managers want to realize their activities and make decisions by analyzing these data. BDA has become important in this regard. Basically, BDA is the process of filtering data with terabytes of small values into the high-valued data, and in some cases even a high-valued single-bit data. The goal here is to see the bigger picture of our digital life (Fisher et al., 2012, p.50).

Big data is considered as data that exceeds processing capacity of traditional database systems. This data is too big, multiplying very rapidly and is not compatible for existing database systems. Therefore, firms need alternative analytical techniques to process data and to take the information in big data sets (Dumbill, 2013). In this context, BDA capabilities become important for companies to transform information in big data into strategic resources and creating new strategies to meet customer needs and expectations (Davenport & Patil, 2012).

In the literature there are many definitions for BDA capability. Generally it is seen as the firms' ability to manage a huge volume of disparate data to allow users to implement data analysis and reaction (Hurwitz et al., 2013). Kwon et al. (2014, p.387) define BDA as "technologies (e.g., database and data mining tools) and techniques (e.g., analytical methods) that a company can employ to analyze large scale, complex data for various applications intended to augment firm performance in various dimensions". Garmaki, Boughzala and Wamba, (2016) defined BDA capability as "firm's ability to mobilize and deploy BDA resources effectively, utilize BDA resources and align BDA planning with firm strategy to gain competitive advantage and enhance firm performance". In another study, Gupta and George (2016, p.1) defined BDA capability as "firm's ability to assemble, integrate, and deploy its big data-specific resources". Cosic et al., (2012, p.4) define BDA capability as ""the ability to utilize resources to perform a business analytics task, based on the interaction between IT assets and other firm resources." Wamba et al. (2017,

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p.357) treats BDA capability as “an important organizational capability leading to sustainable competitive advantage in the big data environment”.

Theoretically researchers depend on IT capability literature to create BDA capabilities. BDA is seen as a new IT innovation for superior performance and fierce competition (Garmaki et al., 2016). In many studies, IT capabilities are theoretically based on a resource-based viewpoint. Because when creating IT capabilities it is assumed that resources can be easily imitated but capabilities are seen as unique and distinctive for every organization and cannot be easily imitated. Therefore, firms can achieve sustainable competitive advantage with these unique and distinctive capabilities (Santhanam & Hartono, 2003). From this point of view, depending on the resource based view, many researchers have argued that BDA capabilities are important organizational capabilities that provide sustainable competitive advantage to firms (Davenport 2006; Mcafee & Brynjolfsson, 2012; Gupta & George, 2016; Akter et al., 2016; Wamba et al., 2017).

In recent years, it is seen that researchers have given importance to experimental studies that generally investigated BDA capability and firm performance relationship (Garmaki et al. 2016; Akter et al., 2016; Wamba et al., 2017; Gunasekaran et al., 2017) but these researches are not sufficient to create a common understanding of BDA. In order to measure BDA capability researchers generally used information technology (IT) and information systems (IS) capabilities to create BDA capabilities (Garmaki et al., 2016; Gupta & George, 2016; Wang et al., 2016; Wamba et al., 2017; Akter et al., 2016). The table below gives a brief summary of dimensions used in previous BDA capability studies.

Table 02. Big Data Capabilities

McAfee and Brynjolfsson (2012)	Personnel management, corporate decision making and technology
Davenport et al. (2012)	Management, employees and technology
Barton and Court (2012)	Management, technology and data science
Kiron, Prentice and Ferguson (2012)	Organizational culture, analytic platform and analytic capabilities of employees
Gupta and George (2016)	Tangible, human and intangible capabilities
Garmaki et al. (2016)	Technical infrastructure, management, personnel and relational network
Wamba et al. (2017)	Infrastructure flexibility, management and personnel expertise capabiliites
Akter et al. (2016)	Management, technology and talent capabilities
Kwon, Lee and Shin (2014)	Data quality management, data usage experience and acquisition intention of big data analytics
Ji-fan Ren et al. (2017)	BDA system quality, BDA information quality, BDA business value
El-Kassar and Singh (2018)	Big data adoption, routinization and assimilation

3. Research Model and Propositions

In this study we propose technical capability, managerial capability and talent capability dimensions to measure BDA capability. These three dimensions are mostly used ones in the literature. Briefly, technical capability refers to infrastructure elements such as applications, hardware, data, networks, etc. Managerial capability refers to the ability of BDA executives in performing their routines in line with business needs and priorities to manage BDA resources effectively. Talent capability refers to skills and knowledge of

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workers in achieving given tasks (Kim et al., 2012). Researchers in this field generally investigated the relationship between BDA capability and firm performance. For example; Gupta and George (2016), investigated the effect of BDA capability on market performance and operational performance. Chen et al. (2012) investigated the effect of BDA usage on asset productivity and business growth. Kwon et al. (2014) investigated the direct effect of data quality management on data usage experience and adoption intention of big data analytics. Akter et al. (2016) found a positive relationship between BDA capability and firm performance. Unlike other studies we propose a relationship between BDA capability and firm innovativeness with the moderation effect of data-driven culture.

3.1. BDA Capability and Firm Innovativeness

In the big data related studies, researchers generally investigated the relationship between BDA capability and firm performance (e.g. Gupta & George; Chen et al., 2012; Akter et al., 2016). Researchers do not investigated empirically how firm innovativeness will be affected by BDA capabilities. Firm innovativeness generally refers that to what extent organizations are open to new ideas and support innovative activities (Hurley & Hult, 1998; Calantone et al., 2002). In this study we propose a relationship between BDA capability and firm innovativeness.

LaValle et al. (2011) pointed out that top-performing organizations use analytics five times more than lower performers. That is why big data usage makes companies more competitive. They create new products and services according to the results of big data analyses. Manufacturing firms use data from actual product consumptions to create new innovative products, improve existing products and develop next generations of products. Also, firms can invent new business models or improve existing business processes depending on the big data analyses results. As a result big data usage becomes important for companies to outperform their rivals by creating sustainable competitive advantage in the long run. For this reason, forward thinking leaders have given importance to build big data capabilities in the entire organization (Manyika et al, 2011).

As it is mentioned above, when researchers create BDA capabilities in their studies they generally depend on IT literature and created their BDA capability measures on the basis of IT capability measures (e.g. Garmaki et al., 2016; Gupta and George, 2016; Wang et al., 2016). When we examine IT capability literature, it is understood that IT facilitates innovation processes by improving communication, knowledge sharing and organizational learning. Also, IT usage is expected to reduce development cost and shorten development process of new products and services (Carbonara, 2005; Banker et al., 2006). Similarly, today’s managers and researchers put great emphasis on big data as a driver for innovation and competitive advantage (Tan et al., 2015). In the big data literature it is assumed that firms can create new innovative products, improve existing products and develop next generations of products depending on the actual consumption data of existing products. This means that especially manufacturing firms use big data sets from different sources to create new products, new business models or processes (Manyika et al., 2011). Erevelles et al. (2007) states that in highly competitive marketplaces, to achieve competitive advantage firms must enhance idea generation speed. In this context, big data can be seen as a new competitive source of idea generation in new product development, distribution channels, dynamic pricing, customer service and so on (Erevelles et al., 2016). Based on this logic, we state the following proposition:

P1: BDA capabilities are positively related to firm innovativeness.

3.2. Moderating Role of Data-Driven Culture

Beyond the necessity of technical renewal to adapt big data usage, there exists a great difficulty in managerial and cultural adaption to big data environment. (Brynjolfsson et al., 2012; Wang et al., 2016). Therefore to be successful in big data usage, big data awareness should be settled throughout the firm and big data transformation should be experienced in the entire organization.

Organizational culture generally indicates shared values, norms, assumptions and understandings by members of a social group and this culture has a critical importance for managers to direct employees in the desired way (Schein, 1990; Daft, 2005). In the literature there are many studies takes culture as moderator variable to achieve better firm performance or innovative outcomes (e.g. Hynes, 2009; Prajogo & Ahmed, 2006). With this line, in this study we take data driven culture as a critical factor to enhance the relationship between BDA capability and firm innovativeness. Today, the biggest challenges of big data adoption in companies are managerial and cultural challenges. Companies generally ignore the need for human insight when they adopt big data analytical tools. However, without the acceptance and readiness of whole organization and workers for big data initiatives companies begin to fail (McAfee & Brynjolfsson, 2012). In the literature some researchers pointed out those firms are not always successful in their big data investments. Because these firms do not consider cultural dimension of big data initiatives (Ross et al., 2013; Lavelle et al., 2013). We can say that cultural readiness to big data initiatives is more important than big data applications alone. Data driven culture states a culture where decision makers base their decisions the insights extracted from data rather than their intuitions (Ross et al., 2013; McAfee & Brynjolfsson, 2012).

P2: Data driven culture moderates the relationship between BDA capabilities and firm innovativeness.

In this paper, depending on our literature review and propositions we settled proposed research model as below:

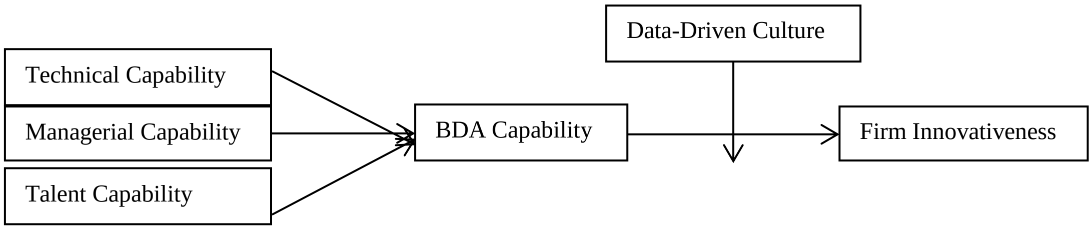

Figure 01. Proposed research model

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4. Conclusions

This study is expected to contribute BDA literature with the development of BDA capabilities and firm innovativeness relationship. Previous studies investigated the effect of BDA capability on firm performance from different perspectives but they haven't examined such a relationship under the moderation of data-driven culture. In this model, we highlight that BDA capability is not sufficient alone to achieve higher innovation performance. Depending on previous literature, we argued that firms need an organization wide mindset to be successful in their big data initiatives and they can achieve this with data-driven culture. Therefore we emphasized the moderating role of data-driven culture in the proposed model. We believe that this model will be an important road map for the researchers and business people in this field. Depending on the given literature review, we expect that empirical researches in the future will support our propositions. When future researchers investigate the proposed model in this paper, they can also investigate the effect of other third variables (such as organizational learning, environmental dynamism, technological turbulence, strategic fit between BDA and business strategy, firm flexibility and so on) on the relationship between BDA capability and innovativeness.

The proposed model has some limitations for empirically testing. Although there are some theoretical contributions about BDA depending on IT and IS literature, empirical studies related to BDA capability are not sufficient enough to measure this variable accurately. The other limitation is related to data collection and sample. To test the proposed research model target sample should be selected from data analysts, business analysts or CIFs because BDA related variables requires technical knowledge from these areas of expertise. Also, accessing the information of this target sample is not easy but it is critical for the accurate measurement of the model.

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