IBN HALDUN UNIVERSITY
GRADUATE SCHOOL OF BUSINESS
MASTER OF ARTS IN MANAGEMENT

MASTER DISSERTATION

BIG DATA ANALYTICS CAPABILITIES AND FIRM PERFORMANCE: AN MCDM APPROACH

MARIAM YASMIN

AUGUST 2019

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APPROVAL PAGE

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Arts in Management (in English).

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ABSTRACT

Big Data Analytics Capabilities and Firm Performance: An MCDM approach

Mariam Yasmin
MA in Management
Thesis Advisor: Prof. Dr. Ekrem Tatoglu
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The digital revolution in the 21st century accentuated the importance of well-established I.S./I.T. departments and decision-making based on insights obtained through big data. The research on big data analytics provides the thematic basis of inquiry for business practitioners and scholars. In this regard, big data analytics capabilities are more likely to provide performance advantages to business firms. Through careful review of the existing literature, it was found that empirical research in big data is at a rudimentary stage. The paucity of empirical studies leaves business professionals into uncharted waters when it comes to implementation and capacity building. It was also observed that the internal mechanisms to devise strategies based on big data analytics are not fully explored. Furthermore, there is a dearth of literature regarding big data analytics capabilities of the firms through dynamic capability view of competitive advantage. This study explored the interdependence of big data analytics capabilities such as infrastructure, human resource, and management capabilities and the impact of these capabilities on firm performance. This study applied both qualitative and quantitative data analysis on the data collected from 8 Chief information technology officers of 08 different firms. The hypothesis of this study was tested through IF-DEMATEL then ANP and TOPSIS (MCDM methods). Results show that big data analytics capabilities are interdependent and Infrastructure capabilities are the most related to firm performance followed by human resource and management capabilities.

Keywords: Analytical network process (ANP), Big data Analytics Capabilities, Dynamic Capabilities, Firm Performance, Multi-criteria decision-making methods (MCDM), Technique for Order-preference by similarity to Ideal Solution (TOPSIS).

ÖZ

Büyük Veri Analitiği Yetenekleri ve Firma Performansı: Bir MCDM yaklaşımı

Mariam Yasmin
İşletme Yüksek Lisans
Tez/Proje Danışmanı: Prof. Dr. Ekrem Tatoğlu
Ağustos 2019, 35 sayfa

21. yüzyıldaki dijital devrim, köklü I.S./I.T. büyük verilerle elde edilen içgörülere dayalı bölümler ve karar alma süreçleri. Büyük veri analitiği üzerine yapılan araştırma, iş pratisyenleri ve akademisyenler için araştırmanın tematik temelini sağlar. Bu bağlamda, büyük veri analitiği yeteneklerinin işletme firmalarına performans avantajları sağlama olasılığı daha yüksektir. Mevcut literatürün dikkatlice incelenmesiyle, büyük verilerdeki ampirik araştırmanın ilkel bir aşamada olduğu tespit edildi. Ampirik çalışmaların azlığı, işletme uzmanlarını, uygulama ve kapasite geliştirme söz konusu olduğunda, keşfedilmemiş sulara bırakmaktadır. Ayrıca, büyük veri analitiklerine dayalı stratejiler geliştirmek için iç mekanizmaların tam olarak araştırılmadığı da gözlemlenmiştir. Ayrıca, firmaların büyük veri analitiği kabiliyetleri konusunda rekabet avantajı dinamik kabiliyet görüşü ile ilgili bir literatür bulunmaktadır. Bu çalışma, altyapı, insan kaynağı ve yönetim yetenekleri gibi büyük veri analitiği yeteneklerinin ve bu yeteneklerin firma performansı üzerindeki etkisinin karşılıklı bağımlılığını araştırdı. Bu çalışma, 08 farklı firmanın 08 Baş bilgi teknolojisi görevlisinden toplanan veriler üzerinde hem nitel hem de nicel veri analizi uygulamıştır. Bu çalışmanın hipotezi IF-DEMATEL, ardından ANP ve TOPSIS (MCDM yöntemleri) ile test edildi. Sonuçlar, büyük veri analizi yeteneklerinin birbirine bağlı olduğunu ve Altyapı yeteneklerinin, en çok insan kaynakları ve yönetim yeteneklerinin takip ettiği firma performansıyla ilgili olduğunu göstermektedir.

Anahtar Kelimeler: Analitik ağ süreci (ANP), Büyük veri Analitik Yetenekleri, Dinamik Yetenekler, Firma Performansı, Çok Kriterli Karar Verme Yöntemleri (MCDM), İdeal Çözüm (TOPSIS) 'e Benzerliği ile Sipariş Tercihleri Tekniği.

DEDICATION

This work is dedicated to my beloved parents for their efforts and affection in raising me and giving the best gift of education.

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I would like to thank Prof. Dr. Ekrem Tatoglu, my thesis supervisor and academic advisor for his kind supervision and support in writing this thesis.

MARIAM YASMIN
ISTANBUL, 2019

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LIST OF SYMBOLS AND ABBREVIATIONS

AHP	Analytical hierarchal process
ANP	Analytical network process
APICS	American Production and Inventory Control Society
BD	Big Data
BDA	Big data analytics
BDAC	Big Data Analytics Capabilities
BDD	Big data-driven
BDS	Big data-savvy
BPM	Business Process Management
CART	Classification and Regression trees
CBR	Case-based reasoning
CTO	Chief technical officer
DBMS	Databases Management System
DC	Dynamic capabilities
DEA	Data envelopment analysis
DEMATEL	Decision-making trial and evolution laboratory
ETL	Extract, Transform, Load
FP	Firm performance
GP	Goal programming
HRM	Human resource management
IEEE	Institute of Electronics and Electrical Engineer
ILM	Information lifecycle management
INFORM	Institute of operation research and the management science
IS	Information System
IT	Information Technology
IoT	Internet of things
KBV	Knowledge-based view
KM	Knowledge management
MAUT	Multi-attribute utility theory
MCDM	Multi-criteria decision methods
OLAP	Online analytical processing
RBV	Resource-based view
SAW	Simple additive weighting
SMART	Simple multi-attribute rating technique
TOPSIS	Technique for the order of preference by similarity to an ideal solution

CHAPTER 1

INTRODUCTION

"Data/information is the oil of the 21st century and analytics is the combustion engine."

Peter Sondergaard,
Senior vice president, Gartner, Inc.

1.1. Introduction to the problem

Gordon Moore, Co-founder of Intel observed in 1965 that transistors per square inch on an integrated circuit had doubled every year since the invention of the integrated circuit in 1959. He also predicted that this tendency will continue in the future. This theory about the exponential growth of processing power of the computer is known as Moore's Law. But in the coming years, processing power and generation of data has grown faster than Moore's prediction. The exponential growth of processing power leads towards the generation of the huge volume of data and storage capacity. The rise of digital technology and disruptive technologies such as the internet of things (IoT), artificial intelligence (AI), and virtual reality (VR) has fundamentally transformed our ways of living and working. This transformation is also regarded as the digital revolution. As soon as the potential advantages of the huge amount of data were realized, the businesses saw an opportunity and adopted the decision-making approach based on information and insights obtained from data in their operations also termed as evidence-based decision making.

"Big data" has become a very popular buzzword of this decade and its popularity was fueled by the technological advancements both in software and hardware. Big data analytics is an emerging and a hot topic amongst scholars and business communities since it has outdated the traditional statistical tools and brought value to the firms in both financial and non-financial terms. Big data has grabbed huge attention of both the academics and practitioners as "next big thing" in management and even has been

proposed by some scholars as “next management revolution” (Brynjolfsson & McAfee, 2012) (Ji-fan Ren, Fosso Wamba, Akter, Dubey, & Childe, 2017).
Big data is not just the data or the volume of data. It is about how we analyze and utilize the insights obtained from the data analysis. Big data is generated through multiple sources such as sales, financial transactions, customer contact center, transactional, sensor, and mobile data, traffic monitoring, social media, etc. Then, certain analytical tools are applied to the data to gain insights and useful information from the big data. Researchers have observed the inclined tendency of businesses to use big data applications in their business operations. The big data is already being used in decision-making in firms both in the public and private sectors.

1.2. Background of the study

Numerous white papers, reports in top management magazines and digital companies have been exploring the current and potential applications of big data. Results of second annual survey for the year-2018 of U.S-based informational technology executives on their preferences and outlook on business intelligence and data analytics tools and explored the seven key questions about the data analytics space by sharesPost depicts that large businesses have planned to increase spending on business intelligence and analytics tool from 88% to 93% and small businesses from 86% to 91%. The percentage of IT professionals using predictive and descriptive analytics elevated from the 40s to 60s over the course of a year and usage of content analytics reached up to 54% from 43%. Almost all the companies in the survey aim to reduce the dependence on external sources and develop in-house capabilities and the companies who already have those capabilities have plans to grow their HR capabilities in the coming years. Renowned analytics companies i.e. Tableau, Splunk and Qlik are winning more customer. Since last year, the number of customers for Tableau has increased from 18 to 33%. Splunk from 19% to 22% and Qlik from 8% to 11% (Phillips, Nara, & Kulkarni, 2019).

Gartner CIO agenda report-2016 includes a survey of 2,944 CIOs across 84 countries around the globe reveals that digitalization is boosting. CIOs anticipates the growth of digital revenue from 16% to 37% in the following five years. Likewise, public sector CIOs are expecting a rise in digital processes from 42% to 77%. This report highlighted some obstacles-talent gap being the biggest obstacle standing in ways of CIOs to achieve their digitization aims. Talent gaps around the information are big data, analytics, and information management. The reason could be the slower pace of talent management practices as compared to continuous and fast-paced growth in the digital world (Gartner, 2016).

Applications of big data are limitless. Big data is applicable to healthcare, education, tourism, transportation, agriculture, public service, retail, manufacturing, banking, insurance, financial, energy sectors, etc.

The industrial internet is a combination of "big data analytics" and "internet of things". GE and Accenture conducted a survey in 7 countries that includes China, France, Germany, India, South Africa, United Kingdom and United States that covered 08 industries i.e. Aviation, Wind, Power Generation, Power Distribution, Oil and Gas, Rail, Manufacturing, and Mining to explore that big data analytics is the substance of Industrial Internet. The research found out that 73% of the companies surveyed are already investing above 20% and more than 2 of 10 are investing above 30% of overall technology budget in big data analytics and 76% of the respondents believe it to be increased in the following year. According to 53% of the respondents, the board of the directors influenced the big data adoption strategy, chief executive officer favored by 47%. Further, the research proposes aggregate of the following actions i.e. take the exponential growth in data volumes, add to the internet of things, add growing technology capabilities in analytics, and add the context of industry yields the industrial internet. The focus of talent acquisition and development is another key area emphasized in this research. 63% of the executives believed that hiring talent with requisite expertise is inevitable to fix the challenge of talent gap. (Accenture & GE, 2015)

1.3. Purpose of the study

William Edward Deming says "In God, we trust: all others bring data".

Big data is an asset. Big data is a driver of business success factors and a source of competitive advantage. Big data has features to influence the innovation and performance of the firms. The modern BDA techniques used are data mining, predictive analytics, machine learning, and text analytics. In some opposing views, it is believed that modern techniques such as artificial intelligence have replaced the jobs performed by a human. But the truth is that the purpose of technological advancement is to facilitate jobs performed by human not to replace or eradicate altogether.

Growth of big data, advanced algorithms, and improved computing power, storage and speed have empowered the artificial intelligence. Artificial intelligence is one of the countless ways big data can be used as it makes data meaningful through cognitive computing. Artificial intelligence and other modern technologies are meant to augment technology-human interaction not to replace human contributions (Duan, Edwards, & Dwivedi, 2019).

1.4. Rationale

Around the globe, propensity to apply big data analytics to devise strategies in most of the business functions that create value, competitive advantage and innovation instead of relying much on intuition and experience for effective decision making and ultimately better firm performance. Researchers are providing strategic and practical guidelines to benefit from big data. However, the application perspective of big data through rigorous academic investigation and theorization are still in process. Moreover, the internal mechanisms to devise strategies based on big data analytics is not fully explored. To date, numerous researchers have studied the advantages of big data analytics in connection with the financial and non-financial performance, its adoption is still at an early stage. To enlarge this stream of research, this study contributes by the identification of sets of big data analytics capabilities such as infrastructure, management, and HRM, the interdependence of those capabilities and their relative significance to firm's performance.

In terms of evidence-based decision-making, big data analytics has a long way to go. The prevalent culture of decision-making is based on the gut, intuition, and experience of the person-in-charge also known as the highest-paid person. To curb these practices, the organization needs to adopt strategies that include enhancement of human-technology interaction, alignment of organizational capability athwart the organization, ensuring the quality of data and training of employees at all levels to be well equipped with big data analytics capabilities. An increasing trend in the adoption of big data analytics capabilities has been observed and its impact on the performance of the organization has also been reported in the literature. Numerous researches, regarding big data as a resource, has explored the relationship under the theoretical framework of the resource-based view of competitive advantage by Professor Jay J. Barney, Professor in Strategic Management. However, scarcity in the literature regarding the investigation of management and potential benefits of big data through the lens of knowledge-based view and dynamic capability perspective was observed.

This study has methodically explored the nomenclature of theoretical frameworks of competitive advantage in strategic management literature in the context of modern-day business scenario and practices. Keeping in view the turbulent nature of the business environment and incessant competition this study underpins the big data analytics capabilities as dynamic capabilities of the firm.

1.5. Statement of the problem

Big data has been gaining momentum for the past decade. But conceptualization of the concept of big data is prevalent in big data literature. The empirical research is at a rudimentary stage. The paucity of empirical studies leaves professionals into uncharted waters when it comes to implementation and capacity building. Multidimensional capabilities of the firms in information technology and information system have been a debate in big data literature. The most interesting and baffling question in Big data research is about what capabilities to acquire to get ahead in big data efforts? Whether to acquire technical or non-technical capabilities? This study also emphasizes the cross-functional application of big data analytics. The available empirical studies highlight the three capabilities (Infrastructure, HR and management) of vital importance with the emphasis on favorable organizational infrastructure.

The individuality of this study is in its approach to explore the interdependence of aforementioned capabilities and their influence on firm performance by applying ANP (analytical network processing), the multicriteria decision modeling technique and DEMATEL (decision-making trial and evaluation laboratory) methodologies. The aim of these methodologies is to explore the hierarchical relationship and interdependence of these capabilities. The information system/big data literature was found to be lacking studies using multicriteria decision modeling. However, (Kamali et al., 2018) explored that challenges associated with IoT development in Iran by applying fuzzy analytical network processing (FANP) and the findings were limited to challenges faced by the external environment.

Firms such as Google, Uber, Amazon, etc. have business models based on big data and analytics. But the situation of firms that has traditional business model is different. Thus, this study limited its sample to firms with traditional business models. The sample size for this study was deliberately kept limited to the firms that are operating in the market for the past 40 and above years. The rationale behind this criterion was that the firms that are above 40 years old must have gone through technological transformation. These transformations require efforts, investment, and top management's attitude towards adaptability and understanding of the expected outcomes of certain technological transformations. Moreover, technological transformation demands challenges related to human resources such as skillset of current employees, training of current employees about new technology and system, hiring of new employees with requisite knowledge and skillset.

1.6. Significance of the study

This study enlarges two independent streams of research 1) strategic: by focusing on the theoretical framework such as RBV, KBV, Dynamic capabilities and 2) empirical: by focusing on the statistics. This study has threefold purposes, first, insights of theories of competitive advantage in strategic management literature in connection with big data. Second, to identify significant factors of three big data analytics capabilities; Infrastructure, Management, and Human Resource Management. Third, to measure the hierarchical relationship between big data analytics capabilities and firm performance.

This study aims at exploring the big data analytics capabilities of the firms operating in Faisalabad, the third largest industrial city of Pakistan. This city is mainly dominated by the textile industry. So, the majority of the firms in the sample are in the textile business. All the firms in the sample all involved in exports. International customers have certain requirements for their manufacturers. This study also explored how customers have an impact on pushing customers to build big data analytics capabilities.

1.7. Organization of the study

This dissertation comprises of four chapters. Chapter 1 introduces the problem, highlights the problem statement and rationale. Chapter-2 reviews the pertinent literature, explores the theoretical framework of competitive advantage and presents the proposed conceptual model, chapter-3 explains the data collection, research methodologies applied, and results obtained through data analysis. Chapter-4 consists of the discussion of findings and conclusion.

CHAPTER 2

LITERATURE REVIEW

This chapter, after reviewing the pertinent literature, provides the history of the evolution of big data over the course of time, defines the key constructs of this study, shortlists the most relevant big data analytics capabilities, and illustrates the summary of existing literature exploring the association of big data analytics capabilities with firm performance. Moreover, after careful scrutiny of pertinent literature, a research framework has been proposed to test empirically.

2.1. Evolution of Big Data and Big Data Analytics

(H.P.Luhn, 1958) a researcher in Computer sciences, library and information system of IBM also known as the creator of Luhn algorithm or Luhn formula developed an automatic system to disseminating information to various departments of any industrial, scientific or government organization and called it business intelligence system. In his proposal, Luhn emphasized to optimize business by using data (Santos et al., 2017). The term “big data” was first used by two researchers ar NASA, Michael Cox and David Ellsworth in 1997 in a paper presented at an IEEE conference that discusses the challenges of computer technologies and large volumes of data (Cox & Ellsworth, 1997) (Wang, Kung, & Byrd, 2018). (Diebold, 2012) claims the root of the term “big data” on the lunch-table conversations by John Mashey, Chief Scientist at Silicon Graphics Inc. (SGI) in the mid-1990s as per the research of a Ph.D. candidate at Technical University of Freiberg named Marco Pospiech. But the latter claim is based on unpublished and non-academic work.

In the 1940s, optimization and simulation techniques were developed to take full advantage of the limited resources. The 1960s and 1970s was the period of the progress of the “management information system” and “decision support system” that promoted the idea of analytics and eventually grown into operational research, machine learning and information system. It is a climate of opinion amongst researchers and practitioners that the modified terminologies for business analytics such as "big data" and "tools/techniques used for big data analysis" that includes deep learning, image processing, text mining, and sentiment analysis are simply "buzz words" but the purpose is still the same (Delen & Zolbanin, 2018).

2001 to 2008 was an evolutionary period for the growth of big data. Initially, big data was characterized in the framework of 3 Vs (volume, velocity, and variety). Later, the development of more sophisticated software abetted the better utilization of information. 2009 was the "year of revolution in big data analytics" fortified with the innovation of big-data computing (Wang et al., 2018).

In the 2010s, the terminology artificial intelligence returned to popularity with the growth in big data understanding and application. Other terms such as "data mining" and "machine learning" are also prevalent these days. "Data mining" has its roots in the field of economics and is a rather new terminology as it only ran rife after the mid-1990s. Machine learning is seen as a more technical jargon. Changes in terminology are simply "Fashion". For instance, the CART decision tree approach is used in the data mining technique is simply a rule induction algorithm in the 1990s, business rules were known as production rules in 1980s and 1990s, and expert systems, knowledge-based systems, intelligent decision support system, intelligent software agent systems, intelligent executive systems, and AI systems are identical (Duan et al., 2019).

(Chaudhuri, Dayal, & Narasayya, 2011) referred "big data analytics to the business intelligence and analytics technologies mostly related to data mining and statistical analysis that relies on commercial technologies such as DBMS (data-based management system), data warehousing, ETL (extract, transform, load), OLAP (online analytical processing) and BPM (business process management)."

(Chen, Hsinchun, Roger H. L. Chiang, 2012) asserted the evolution of BI from BI&A to big data. Authors further explained that the term business analytics was used to describe key analytical components of BI whereas big data was used for large and convoluted datasets that require exclusive data storage, analysis, and visualization techniques and technologies. (Ji-fan Ren et al., 2017) endorsed definition of big data by (APICS, 2012) as below:

> "A collection of data and technology that accesses integrates, and reports all the available data by filtering, correlating and reporting insights not attainable with past data technologies."

Definition of Big data by TechAmerica Foundation is as below:

> "Big data is a term that describes large volumes of high velocity. Complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of information".

Big data as defined by (Manyika et al., 2011):

> "Datasets with the size beyond the capacity of typical databases software tools to capture, store, manage and analyze.".

(Boyd & Crawford, 2012) defines big data as:

> "A cultural, technological and scholarly phenomenon that is supported by the interplay of (i) Technology: maximizing computation power and algorithmic accuracy to gather, analyze, link, and compare large data sets. (ii) Analysis: drawing on large data sets to identify patterns in order to make economic, social, technical and legal claims. (3) Mythology: the widespread belief that large data sets offer a higher form of intelligence and knowledge that can generate insights that were previously impossible, with the aura of truth, objectivity, and accuracy."

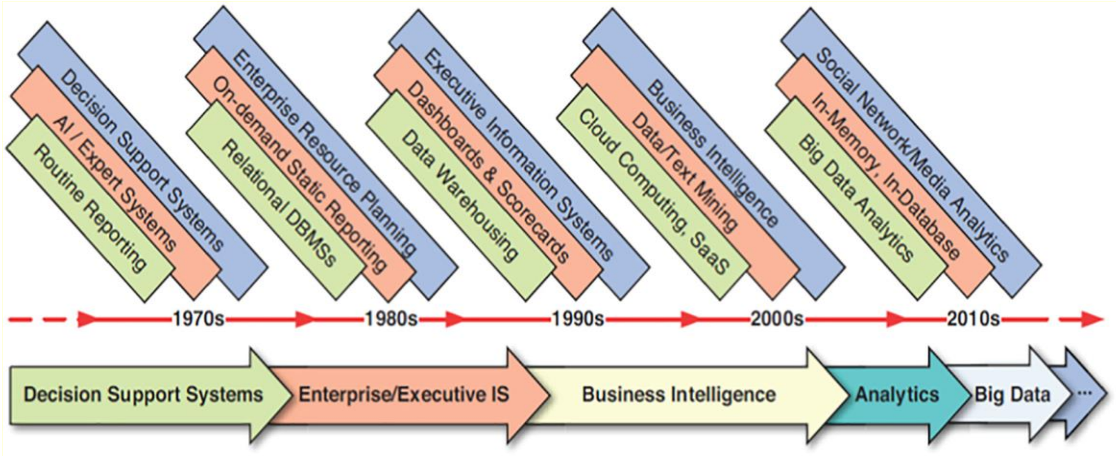

Fig 2.1 Evolution of Big Data (Delen & Zolbanin, 2018)

(Fosso Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015) presented a broader picture of "big data" and defined as:

> "A holistic approach to manage, process and analyze 5 Vs (volume, variety, velocity, veracity, and value) to create actionable insights for sustained value delivery, measuring performance and competitive advantages."

Definition of Big Data in Gartner IT glossary is "high volume, high velocity and/or high variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation" (Gartner 2019). (T. Davenport & Harris, 2017) defined analytics as below:

> "The extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions."

2.2. Big data defined in 5Vs framework

A general misconception of big data is data of huge size or volume. Nonetheless, the literature defines big data in terms of five dimensions also known as 5Vs; volume, velocity, variety, veracity, and value. **Volume** attributes to the size of data generated on a daily basis. Technological advancement leads towards the exponential growth of data larger than the storage capability. **Velocity** designates the speed of data generation. Nowadays, technological advancement has made possible to access real-time or nearly real-time data. Keeping in view the incessant competition in the markets, decision-making processes at the firm level must be agile and fast. **Variety** denotes the generation of data through numerous digital platforms. Through their inputs on electronic gadgets and social media platforms, users provide information about their preferences, needs, habits, location and more. **Veracity** is about the quality of data and a trust level for the original source of data creation because data could be outdated, irrelevant, incomplete or simply noise. **Value** is about the capability of the firm to utilize the data and make evidence-based decision-making effectively drawn on the data (Ferraris, Mazzoleni, Devalle, & Couturier, 2018).

2.3. Big data-processes and technologies

(Gandomi & Haider, 2015) proposed a two-stage model further broken down to 5 sub-stages called big-data process for extracting insights from big data. The first stage i.e. data management consists of three sub-stages that involves the acquisition and storage of data, extraction, cleaning and annotation, and integration, aggregation and representation. The second stage i.e. analytics involves modeling, analysis, and interpretation of information acquired from big data.

(Liberatore & Luo, 2010) categorized process of data analysis into four stages. First, collection, extraction, and manipulation of data. The second stage is about summarizing and visualization of the data by applying various analytical tools and techniques. The third stage is about extracting insightful information through the output of visualization and models. At last decisions are taken based on the insights and strategies are designed and modified accordingly.

Three foremost technologies associated with big data are Hadoop: an open-source network that process, store, and analyze huge amount of unstructured data; NoSQL databases: allows the stored discrete data among sizes of data to end-users and automated big-data applications; massively parallel analytics databases: enables ingesting, processing and enquiring of data through multiple machines and processes (Ferraris et al., 2018).

2.4. Taxonomy of Analytics

The most common taxonomy of analytics can be divided into three dimensions such as descriptive, predictive, prescriptive. These dimensions are autonomous as each of these is associated with different ranges of functions and problems in an organization.

> “**Descriptive analytics** also known as business intelligence or performance reporting provides access to historical and current data. It provides the ability to alert, explore, and report using both internal and external data from a variety of sources.
>
> **Predictive analytics** uses quantitative techniques (propensity, segmentation, network analysis, and econometric forecasting) and technologies (such as models and rule-based systems) that uses past data to predict the future.
>
> **Prescriptive analytics** uses a variety of quantitative techniques (such as optimization) and technologies (models, machine learning, and recommendation engines) to specify optimal behaviors and actions.
>
> **Autonomous analytics** employs artificial intelligence and cognitive technologies (machine learning) to create and improve models and learn from data-all without human hypotheses and with substantially less involvement by human analysts” (T. Davenport & Harris, 2017).

2.5. Big Data Analytics Capabilities

Eminent scholars around the globe emphasize the significance of the broader view of big data analytics capabilities to maximize the benefits out of it.

(Akhtar, Frynas, & Mellahi, 2019) define big data capabilities as:

> “An effective combination of relevant human resource, pre-requisite big data skills (both functional and team-based skills), advanced technologies, mathematical and statistical techniques, and machine learning tools that produce and process large datasets to generate analytical reports and actionable insights utilized for improving performance.”

(Ji-fan Ren et al., 2017) and (Mikalef, Boura, Lekakos, & Krogstie, 2019) defined big data analytics capabilities as:

> “The ability of the firm to capture and analyze data towards the generation of insights by effectively deploying its data, technology, and talent through firm-wide processes, roles, and structures.”

(Wang et al., 2018) defined business analytics capability as ILM (information lifecycle management) and endorsed the narration of ILM by (Rogers, Field, & Yoshii, 2009) as stated below:

> “The policies, practices, services, and tools used to align the business value of information with the most appropriate and cost-effective infrastructure from the time when information is created through its final disposition. Information is aligned with business requirements through management policies and service levels associated with applications, metadata, and data.”

(Wang et al., 2018) endorsed the definition of big data analytics with a resource-based view by (Cosic, Shanks, & Maynard, 2012) as below:

> “The ability to utilize resources to perform a business analytics task, based on the interaction between IT assets and other firm resources.”

Five key strategies for success with big data analytics in the healthcare sector are implementing big data governance, developing an information-sharing culture, training key personnel to use big data analytics, incorporating cloud computing into the organization’s big data analytics and generating new ideas from big data analytics.

Moreover, five potential benefits driven from big data analytics capabilities are IT infrastructure, operational, organizational, managerial and strategic benefits based on five big data analytics capability identified as analytical capability for patterns of care, unstructured data analytical capability, decision support capability, predictive capability and traceability (Wang et al., 2018).

Merely 4% out of 400 companies around the globe have capabilities i.e. right people, tools, data intentional focus and analytical insights and these firms were performing better in terms of both financial and non-financial performance. Four areas are crucial for building up data analytics capabilities of firms i.e. data-savvy people, quality data, state-of-the-art tools and processes and incentives that support analytical decision making (Wegener & Sinha, 2013).

(Brynjolfsson & McAfee, 2012) conducted a research along with colleagues to test the hypothesis that data-driven companies would be better performers through structured interviews with executives of 330 public North American companies about their technology and management practices and made a comparison with the performance based on the data from their annual reports and other independent resources. Findings of the study were that not all the firms were data-driven and on average, the data-driven firms were 5% more productive and 6% more profitable than their competitors.

(Brynjolfsson & McAfee, 2012) argues about the significance of the combination of infrastructure, human resource and management capabilities of firms for successful adaption of BDA and superior financial and operational performance. They further argued that the technical challenge of using big data is a real but managerial challenge is even greater dealing from top to bottom of the organizational hierarchy. firms will not be able to take full advantage of big data unless they do not manage the change effectively. To cope up with this challenge, they proposed five areas for firms to focus more i.e. leadership, talent management, technology, decision making, and company culture. (Barton & Court, 2012) supported the idea of the interconnection of technology, people and management in a big data environment also emphasized upon the integrated approach to data sourcing, model building and organizational transformation to benefit from big data.

(Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016) categorized big data analytics capabilities into three typologies i.e. big data analytics management capabilities, big data analytics technology capabilities, and big data analytics talent capabilities. (Cosic et al., 2012) categorized business analytics capabilities into four categories as governance, culture, people, and technology.

Adoption of big data analytics capabilities involves a three-stage process; acceptance, assimilation, and routinization incorporated with corporate commitment. Acceptance is about the acknowledgment of technologies by stakeholders. Routinization is about organizational structure that embeds the technologies into the processes. Integration is how well technology is embedded and spread across the organization functions and how much is it aligned with goals and strategies of the firm (D. J. Teece, 2003) (Singh & El-Kassar, 2019).

(Wang, Kung, Gupta, & Ozdemir, 2019) highlighted the sets of primary BDA capabilities such as data integration, analytical, analytical person, predictive, data interpretation capabilities and complementary organizational resources such as evidence-based decision making, data governance, improvisational and planned dynamic capabilities.

Existing literature stresses the three BDA capabilities (infrastructure, management, and human resource capabilities) of the firms required for the better financial and non-financial performance of the firms.

2.6. Big data Analytics capabilities and Firm Performance

"You cannot manage what you do not measure" wise words attributed to both William Edwards Deming and Peter Ferdinand Drucker, explains why the big data and big data analytics are crucial for business practices in the modern era.

A significant number of research studies in the past have explored the positive relationship of big data analytics capabilities of firms and firm performance. The scholars and practitioners agreed upon the significance of evidence-based decision making and the data analysis is reliable evidence for efficient decision making. Big data analytics capabilities are holistic in its nature and cover all business functions. The efficient decision-making backed up by evidence aids better preparation for business operation ranging from running daily operations to devising future strategies including promotional and marketing activities, investment decision, managing supply chain, etc.

(Ferraris et al., 2018) conducted an empirical analysis of the data collected from Italian firms and concluded that decisions based on big data are likely to be effective decisions consequently lean towards better firm performance. Moreover, knowledge management moderates in magnifying the impact on big data analytics capabilities. So, recommended that top management needs to acknowledge this and change the managerial approach, hire and train existing employees.

(Akter et al., 2016) explored the mediating role of business strategy alignment in firm performance through big data analytics capabilities. (Bharadawaj, 2000) investigated significant and positive association between IT capabilities and firm performance. Performance management, customer management, and process management capabilities play the role of moderator in the positive relationship between information management capabilities and firm performance.

(Amankwah-Amoah & Adomako, 2019) adopted a different approach to studying the impact of big data analytics on firm performance by developing a four-domain framework that explains how different approaches towards big data analytics adoption and implementation can lead towards different outcomes i.e. failure. Furthermore, firms that possess ordinary big data analytics capabilities and mere data more likely creates business failure.

Identification of strategic and business value of the big data analytics is the key. To be successful in implementation of big data analytics in healthcare setting, five strategies are recommended; 1) implementation of big data governance, 2) creation of information sharing culture, 3) training of key personnel to use big data analytics, 4) integration of cloud computing into organization’s big data analytics, 5) generation of new business ideas from big data analytics (Wang et al., 2018).

(Akhtar et al., 2019) explored the significant positive relation between BDS (big data-savvy) teams, BDD (big data-driven) actions and firm performance. Further, identified the skills and techniques used by BDS savvy teams such as MapReduce, Hadoop, decision trees, basket analysis, machine learning, statistics, mathematics, computing, operations research, information management business intelligence, data mining skill (classification, clustering, regression, association and neuro network analysis) that entails the understanding of popular algorithms- K-means, support vector machine, Apriori, expectation-maximization, PageRank, AdaBoost, K-nearest neighbors, naïve Bayes, and CART. Some other relevant skills such as statistical machine learning based on several techniques that take in Bayesian networks, reinforcement learning, hidden Markov models and process mining-used for web analytics, text mining and supply chain mapping. It is unlikely to all be known by one professional, so, authors emphasized the diversity of skills and knowledge of BDS teams.

Big data analytics capabilities such as tangible, intangible and human skills have a positive association with innovation with the mediating role of dynamic capabilities and moderating role of factors from the environment such as dynamism, heterogeneity, and hostility. An organizational culture that deploys resources synergistically and relies on evidence-based decision making produces more competitive performance gains (Mikalef et al., 2019).

2.7. Theoretical Framework

The scholars of strategic management have studied the sources of competitive advantages and have advocated that data, information, and knowledge are sources of competitive advantage. There is still debate about the most suitable theoretical approach of competitive advantage. The debate pertains to the questions that either big data is a source or a capability, either insights or information obtained through big data analytics are regarded as resource or knowledge, either big data analytics capabilities are resource, dynamic capabilities or knowledge management. This study cautiously explored the nomenclature of the most discussed theoretical frameworks in literature.

2.7.1 Resource-based view

The resource-based view of the firm articulates two alternate sources of competitive advantage. The first source is the heterogeneity of the firms in terms of strategic resources. The second source is the perfect immobility of these resources across the firms and may result in long-lasting heterogeneity. Numerous authors have identified multiple resources of firms as a source of competitive advantage. These sources can be classified into three categories: physical capital resources, human capital resources, and organizational capital resources. Physical capital resources are physical technological equipment of firms such as plant, machinery, equipment, region, and access to raw material. Human capital resources can be attributed as the intangible resources such as training, experience, judgment, intelligence, relationship, and insight of employees in the firm. Organizational capital resources include the firm's reporting structure, formal and informal planning, controlling, and coordinating, in addition, informal relations among groups within firm and firms operating in the industry. Attributes of the firms lead to sustainable competitive advantage can be categorized as valuable, rare, imperfectly imitable, and non-substitutable (Barney, 1991).

A firm's managerial talent is vital for the implementation of value-creating strategy as it distinguishes it from other firms in competition. Effective combination of firm's physical capital, human capital and organizational capital resources in the implementation of strategies is a rare resource and can be imperfectly imitable (Hambrick, 1987).

Resources are defined as assets, knowledge, capabilities, and processes. (Grant, 1991) distinguishes between resources and capabilities and further classified resources into three categories, tangible, intangible and personnel based. Numerous scholars argued that a unique set of IT capabilities and managerial skills that create value for the firm are firm-specific and imitable. Imitability of firm's resources can be avoided in the nexus of interpersonal relations among managers, firm's culture, firm's reputation among suppliers and customers, and information processing systems. This phenomenon of social complexity adds value to the firm (Barney, 1991).

2.7.2 Knowledge-based view

A simple definition of a knowledge-based system is “a system that represents knowledge”. The term knowledge-based system became popular after the Alvey program of IT research in 1982/3 by Government of UK. At that time, some scholars consider the expert system as a sub-set of the knowledge-based system, on the other hand, some viewed these two terms corresponding. At the advent of the 21st century, the knowledge-based system substituted expert system in business and management but in other domains like sciences and engineering, the expert system is still dominant. There are three plausible reasons for this substitution; first, “expert system” was no more attractive label because of the bad reputation some expert system projects earned. Second, the comprehension that the role of the system is to assist humans in decision making not to tell them what to do. Third, in the 1990s, the increasing popularity of knowledge management leads towards the replacement of “the knowledge” with “the expert” (Duan et al., 2019).

(Faucher, Everett, & Lawson, 2008) postulated that data, information, knowledge, and wisdom are distinct categories and cannot be mixed. Difference between data and information is not structural but functional. (Ackoff, 1989) posed that knowledge system is non-linear and result of interaction between the data, information, and knowledge regardless of the levels of hierarchy such as individual, group or organizational level. Further, emphasized to explore knowledge management beyond the hierarchical relationship between data, information, knowledge, and wisdom in the light of complexity theory. Data is the basic unit of knowledge management.

Figure 2.2. Traditional Knowledge pyramid (Faucher et al., 2008)

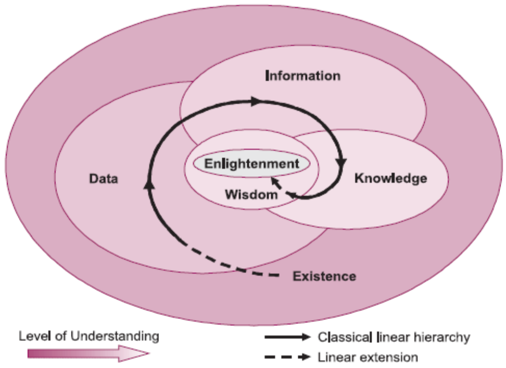

Fıg. 2.3 Complexity-based view of knowledge system (Faucher et al., 2008)

(Williams, 2006) characterized knowledge as "dynamic, strategic, political and subject to change". Theory of organization assumes that the ultimate task of an organization is to effectively deal with information and to dynamically deal with environmental uncertainty. A dynamic theory of organizational learning stances that organizational knowledge is generated through an interplay of two dimensions of knowledge creation; "implicit knowledge" and "explicit knowledge" by means of four modes also known as SECI model of knowledge creation; socialization, externalization, internalization, a combination that drives innovation (Nonaka, 1994).

2.7.3 Dynamic Capabilities

(D. Teece & Pisano, 1994) highlights shortcomings of resource-based view as it is relatively static and is not compatible with the rapidly changing business environment and conceptualized dynamic capabilities to prevail over the shortcomings of the resource-based view. Dynamic capabilities encompass three organizational practices i.e. sensing, seizing and configuration. These capabilities enable organizations to respond to rapidly adapt the changes in the business environment and update their resource base. The IS literature sets a distinction between IT sources i.e. IT resources including computer network, hardware, software, data, and other organizational sources i.e. people, processes and routines (Cosic et al., 2012).

Struggle to develop new capabilities and advance in existing ones is crucial in Schumpeterian world. (D. Teece & Pisano, 1994) described competition through dynamic capability view based on Schumpeterian theory. Further, proclaimed that the source of competitive advantage is “dynamic capabilities” based on the notion that competitive advantage entails both the exploitation of existing internal and external firm-specific capabilities and of flourishing new ones. Scholars agreed that distinctive resources that are difficult to imitate are a source of competitive advantage. The fundamental idea of dynamic capability is tacit knowledge; nexus of coordinative management processes because behavior, processes, and operations of a firm are difficult to replicate even though the coherence is observable.

(Ferraris et al., 2018) accentuated the consideration of two vital capabilities of firms connected to the human side of big data: big data analytics and knowledge management. Dynamic capability can create or add value to the business by modifying the way of conducting business.

Big data analytics capabilities qualify firms to see the patterns of decision making in the past and future as well. This qualification minimizes the human-error in decision making and ultimately reduces the risk. The facility to forecast the future based on data builds an ability to respond quickly to the fluctuations in the business environment thus enables firms to gain competitive advantage, financial and non-financial profits and more importantly building dynamic capabilities.

Data is a resource but static and of no use in a vacuum unless converted into useful information. Since, the very nature of big data analytics capabilities is acquisition, conversion, and application of knowledge in the form of data and information. That favors the knowledge-based view of the firm and the ability to create a data-driven decision-making environment explains the dynamic capability of the firms.

2.7.4 Entanglement view of Socio-materialism

Socio-materiality refers to the amalgamation of social and material. The entanglement view of socio-materialism embraces that organizational capabilities such as management, infrastructure, and human are entwined and individual contribution of these capabilities towards firm performance cannot be measured in isolation. This view is dissimilar with other views such as technological deterministic view (material influences social), social-construction view (social influences the material) and social-technical view (the iterative relationship between social and material). Dimensions of big data analytics capabilities because of their harmonizing features work in synergistic fashion towards firm performance. There is a dearth in the literature regarding the exploration of big data analytics capabilities with the entanglement view of socio-materialism. (Akter et al., 2016). Firm-specific intangible resources such as complementarity and co-specialization of heterogeneous resources in a firm inclined to be tacit, idiosyncratic and interwoven in organizational structure and processes unlike tangible sources such as product attribute that can be replicated. (Powell & Dent-Micallef, 1997) defines complementarity as “the value of one resource is boosted in the presence of other resources”. (Clemons & Row, 2006) defines co-specialization as “one resource has no or little value without other resources”. Data, information, and knowledge are entangled and these synergistic ties contribute towards the elevation of organizational hierarchal resources. (Kallinikos, 2007).

2.7.5 Dynamic Resource-based view

(Helfat & Peteraf, 2003) suggested dynamic resource-based view of competitive advantage that explains the future evolutions of capabilities once they reach or close to the maturity stage. The 6Rs of capability transformation: retirement (death), retrenchment, replication, renewal, redeployment, and recombination occur when selection event intrudes. Hence, the basic idea of dynamic RBV affirms the idea of evolution and dynamicity of resources and capabilities.

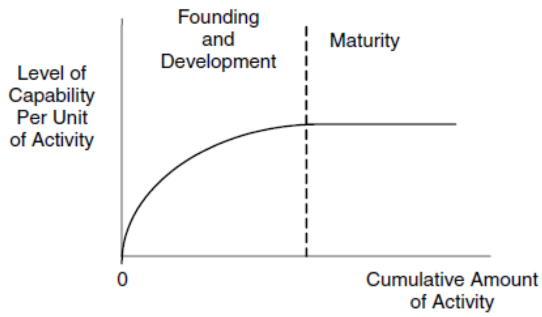

Fig.2.4 Stages of initial capability lifecycle (Helfat & Peteraf, 2003)

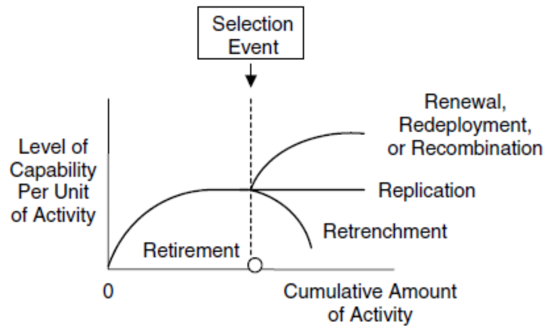

Fig. 2.5 Branches of the capability lifecycle or 6Rs of capability transformation (Helfat & Peteraf, 2003)

2.7.6 Resource-Orchestration Theory

Resource-Orchestration theory is an extension of the resource-based view that explicitly discourses the managerial role to effectively structure, bundle, and leverage the firm's resources. (Sirmon, Hitt, Ireland, & Gilbert, 2011). (Sena, Bhaumik, Sengupta, & Demirbag, 2019) argued that data-driven culture can only be obtained with the strategic alignment between strategy.

David Teece first coined the terminology "complementary assets" and presented a model of complementary assets that highlights two features, first, the imitability same as proposed by Jay Barney. Second, the complementary assets defined as the infrastructure and set of capabilities that generate profitability for the firm through innovation.

Firms must have the stability to continue delivering the value in their idiosyncratic way but agile and adaptive enough to reform as and when needed (Mikalef et al., 2019). (Sena et al., 2019) asserted that with the combination of resources and capabilities, competitive advantage can be achieved. An accurate IT infrastructure and competent workforce are required to add value through Big data analytics. Furthermore, the dynamic capability perspective argues that the right use of capabilities is essentially required to achieve and sustain competitive advantage.

Organizations must evolve with their product lifecycles, so, the organizational capabilities change either organically or in response to changes in the external environment that includes market, industry and disruptive changes in technology. Another shortcoming of RBV is that it does not explain the evolution of resources over time. (Sena et al., 2019) supported the argument of dynamic capability perspective of gaining competitive advantage through big data and proposed that certain dimensions of capabilities such as coordinating and reconfiguring capability are generated through big data. Further, characterized the coordinating capability as synchronization of internal resources and processes and reconfiguring capability as adoption and modification in response to changes in the external environment.

Data is a resource. But data is a pile of numbers and a vacuum. Data needs to be utilized to gain insights and information for decision-making and for that very purpose certain analytical tools are applied on data. Data can both be beneficial and catastrophic. It only benefits when firms develop certain capabilities to utilize it. Developing those capabilities is insufficient unless capabilities and system are integrated.

The points of commonality in the above theories of competitive advantage are inimitability and synchronization of resources, processes, and capabilities. But for survival in a turbulent business environment, adaptability and evolution is the key. Since, the theory of dynamic capability in addition to the acknowledgment of inimitability and synchronization of resources, processes, and capabilities, embraces the dynamicity of resources, business operation, and capabilities. The theory of dynamic capability stresses the evolution of competitive resources and capabilities in response to the changes in the internal and external department. It is pertinent to mention the responsiveness towards technological transformations in the digital age. Moreover, big data analytics capabilities of the firm provide an environment of closely knitted business functions. The “tacit knowledge” acquired through an environment where business functions are closely knitted and synchronized is difficult to imitate by competitors. This study underpins the dynamic capability view of competitive advantage through knowledge management regarding the insights obtained from big data as “knowledge”.

2.8. Conceptual Model

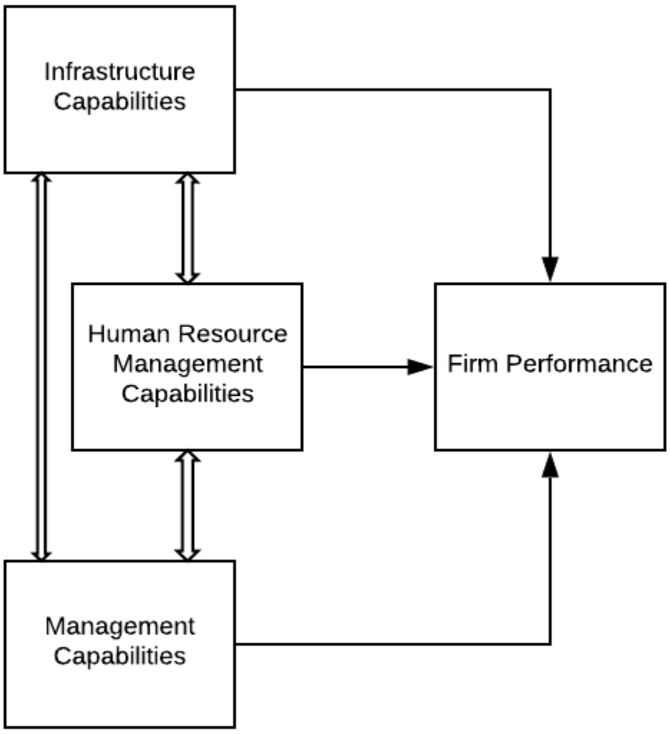

Fig.2.6. Conceptual Model

2.9. Research Questions

Research Question-1

To what extent BDAC are interrelated and interdependent?

Research Question-2

What BDAC are more important than others?

Research Question-3

What BDAC is more related to firm performance?

CHAPTER 3

RESEARCH METHODOLOGY

The application of MCDM methods to organizational decision-making problems is burgeoning.

3.1. Analytical Network Processing (ANP)

Multi-criteria decision-making methods (MCDM) were developed for complex decision-making problems. Most common MCDM are Multi-attribute utility theory (MAUT), analytical hierarchy process (AHP), analytical network process (ANP), Fuzzy set theory, Data envelopment analysis (DEA), case-based reasoning (CBR), simple multi-attribute rating technique (SMART), Goal programming (GP), ELECTRE, PROMETHEE, simple additive weighting (SAW), and Technique for order preferences by similarity to ideal solutions (TOPSIS). MCDM problems involve the choice of criteria and alternative.

Thomas L. Saaty, a distinguished professor at the University of Pittsburgh and inventor of analytical hierarchy process (AHP) proposed analytical network process (ANP). In 2008, Professor Saaty was awarded the "Institute of Operations Research and the Management Science (INFORMS) impact award" for developing AHP.

ANP has been applied in many areas such as sustainability, environmental management, healthcare, construction risk assessment, energy, waste management, supply chain management, etc. Amongst all MCDMs, AHP and ANP are the most commonly used and are found the most effective techniques. (Chen et al., 2019).

ANP splits the system elements into two hierarchies, first, the control hierarchy that consists of problem objectives and decision criteria. All decision criteria in the hierarchy are independent and AHP assigns weights to each criterion. Second, the network hierarchy; comprises of elements controlled by the control hierarchy. The loops in the network show that clusters are interdependent. The pairwise comparison for all the nodes in each cluster to other nodes of the network indicate the preferences of decision-makers.

This study chooses ANP over AHP because ANP is the generalization of AHP and compared to AHP, the ANP is more comprehensive. Furthermore, AHP is a tree-like hierarchical structure but ANP paradigms a network system that fits the research objective of this study.

3.2. The technique for Order Preferences by Similarity to Ideal Solutions (TOPSIS)

TOPSIS is another multicriteria decision method. In TOPSIS, two alternatives are hypothesized and the alternative closest to the ideal situation and farthest from the negative ideal solution. In this study, TOPSIS is applied to find out the relative importance of six criteria of firm performance in connection with big data analytics capabilities.

3.3. Decision Making Trial and Evaluation Laboratory (DEMATEL)

Decision making and evaluation laboratory (DEMATEL), a kind of structural modeling approach aimed at analyzing cause and effect relationship through matrixes or digraphs was first developed at Geneva Research Centre of the Battelle Memorial Institute (Si, You, Liu, & Zhang, 2018). DEMATEL has its applications and has been applied across multiple disciplines such as management decision making, operations research, knowledge management, e-learning, system engineering, causal modeling, and technological innovation. DEMATEL is a multicriteria decision modeling technique that formulizes and analyzes causal relationships amongst complex factor within a structural model to handle the intricacy of human judgments in decision making (Jeng, 2015). Distinguished power of DEMATEL to handle the complexity of decision making made it popular amongst researchers and practitioners in numerous disciplines. Computer Sciences ranks the highest in application followed by Engineering, Business and Management, Decision Sciences, Social Sciences, Mathematics, Environmental Sciences, Medicine, Economics and Econometrics and Energy respectively (Si et al., 2018).

3.4. IF-DEMATEL, ANP, and TOPSIS together:

Sometimes in literature, ANP only is used for decision-making problem. However, the integration of ANP with other MCDM methods such as GP, TOPSIS, DEMATEL, ANN, VIKOR, PROMETHEE, and balanced scorecard has been used by similar nature of problems since it aids solving complex problems. (W. W. Wu, 2008) first applied DEMATEL and ANP combined to evaluate and select knowledge management. Later, the frequency of application of both methodologies combined increased since DEMATEL constructs interrelations among criteria before applying ANP to assign weights to criteria. In literature, the most commonly used DEMATEL technique is a combination of ANP and DEMATEL followed by Classical, Fuzzy and Grey DEMATEL respectively (Si et al., 2018). DEMATEL and ANP complement each other and compensate for each other's weaknesses (Horng, Liu, Chou, Yin, & Tsai, 2014).

The literature on big data highlights the mediating role of organizational culture/infrastructure between big data analytic capabilities and firm performance. Numerous scholars argue that data-driven culture is essential for effective implementation of big data applications. This study aims at exploring the interdependence of big data analytics capabilities. For that purpose, IF-DEMATEL is applied to explore the interdependence of big data analytics capabilities of the firms. Finding the interdependencies between the capabilities is crucial to reveal the important level of factors in complex decision making. Application of ANP in complex decision-making problems ranks the important factors and serves a cause and effect diagram, that effectively demonstrate the connection between factors. At last, TOPSIS was applied to rank the importance of BDAC with firm performance.

An analytical network process is a general form of the analytical hierarchical process used in multicriteria decision modeling. In this model, the analytical network process assembled the capabilities into a hierarchal network. In the existing literature, multicriteria decision modeling techniques have been used mainly for supplier selection.

3.5. Scale Development

For this study, all independent and dependent variables were taken from available literature on big data analytics, information system management, and information technology management. The variables were shortlisted based on their relative importance after discussion with experienced academics and professionals.

The questionnaire was divided into four sections. The first three sections termed infrastructure, human resource and management capabilities; each encompasses five (5) measurement items. The fourth section termed firm performance contains 6 measurement items.

3.6. Data Collection

The Criteria for sample selection was the Chief Technical Officers of the firms listed on the Pakistan Stock Exchange. The rationale behind selecting the Chief Technical Officers as the sample is their knowledge and connection with other business functions as the questionnaire contains the factors involving the overall infrastructure of the firm. The questionnaire along with the cover letter clearly stating the purpose of this study was individually sent to the 40 respondents, 8 respondents returned the questionnaire and agreed for a short interview. The response rate was 20%. The questionnaire was developed and administered in the English language since the official language of Pakistan is English, so the respondents had no difficulty with the language. The firms are located in the city of Faisalabad, the third largest industrial city of Pakistan and the second in the province of Punjab. Textile firms are dominating the market that is why the large proportion of the participant firms are from the textile sector.

Table.3.1. Demographic Characteristics of Respondents:

Number of Respondents	08

Age (Average)	44 years	
Education (Minimum)	Bachelor’s Degree in IT or CS	
Gender	07 Male, 01 Female	
Designation	Chief Technical Officer/ Head of IT Department	
Time to complete the questionnaire (average)	35 minutes	
Affiliation with present firm	0-5 years 5-10 years 11-20 years	12.5% 37.5% 37.5%
Firm Age	11-20 years 31-40 years 40 years and above	25% 62.5% 12.5%
Allocation of IT expenditure in total budget	1-5% 6-10% 11-15% 20%	62.5% 12.5% 12.5% 12.5%
Firm Size (Number of Employees)	1000 and above	100%
Industry	Chemical Textile Petroleum and Energy	25% 62.5% 12.5%
Ownership	Foreign Local	0 100%

3.7. Quantitative analysis (IF-DEMATEL, ANP, TOPSIS)

IF-DEMATEL was applied by using Microsoft Excel to ascertain the connection 15 BDAC criteria. The ‘0’ indicates no relation, ‘1’ indicates a relation as presented in Table.1. The next step is to figure out the relative importance or weight of each criterion. For this purpose, ANP was applied by using the software “Super decision version 2.6.0”. The results of the normalized cluster and priorities after converting into percentage are presented in Table.2. The criteria of BDAC are also ranked in numbers within the cluster and within three clusters of BDAC based on the priority or relative importance ascertained by ANP analysis of criteria within the cluster and within three clusters of BDAC is presented in Table.2.

The results of ANP ranks the infrastructure capabilities the highest followed by human resource management and management capabilities respectively.

Finally, to ascertain the relative association of BDAC with firm performance TOPSIS was performed by using Microsoft Excel. The results obtained through TOPSIS are presented in Table.3.

Table.3.2. Interdependence among nodes and clusters
(obtained through IF-DEMATEL)

	Cr.1	**Cr.2**	**Cr.3**	**Cr.4**	**Cr.5**	**Cr.6**	**Cr.7**	**Cr.8**	**Cr.9**	**Cr.10**	**Cr.11**	**Cr.12**	**Cr.13**	**Cr.14**	**Cr.15**
Cr.1	0	0	1	1	1	0	1	0	1	1	0	0	1	0	1
Cr.2	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0
Cr.3	1	0	0	0	0	1	1	1	1	1	0	0	0	1	0
Cr.4	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0
Cr.5	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Cr.6	0	0	1	1	1	0	0	1	1	1	0	0	1	1	1
Cr.7	0	1	1	1	0	1	0	1	1	1	0	0	1	1	1
Cr.8	0	0	1	0	0	1	1	0	1	1	0	0	0	0	1
Cr.9	0	0	0	0	0	1	1	1	0	1	0	0	1	1	1
Cr.10	1	0	1	0	0	1	1	1	1	0	0	0	1	1	1
Cr.11	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
Cr.12	1	1	1	1	1	1	1	0	0	0	1	0	1	1	1
Cr.13	0	0	1	1	1	0	0	0	0	0	0	1	0	1	1
Cr.14	1	0	0	0	0	0	0	1	1	1	0	0	1	0	1
Cr.15	0	0	1	1	1	0	0	1	1	1	0	1	1	1	0

Table.3.3. Normalized clusters and priorities (in percentage) obtained through ANP

Cluster	**Node**	**Intra-cluster**	**Inter-cluster**	**Overall**	**Ranking within cluster**	**Overall Ranking**
Infrastructure capabilities	Cr.1	22.33	12.04	53.92	3	1
	Cr.2	14.17	7.64		4	
	Cr.3	22.68	12.23		2	
	Cr.4	31.47	16.97		1	
	Cr.5	9.35	5.04		5	
Human Resource Capabilities	Cr.6	27.36	10.45	38.20	1	2
	Cr.7	14.24	5.44		5	
	Cr.8	17.67	6.75		4	
	Cr.9	19.19	7.33		3	
	Cr.10	21.54	8.23		2	
Management Capabilities	Cr.11	0.13	0.01	7.82	5	3
	Cr.12	5.37	0.42		4	
	Cr.13	30.82	2.41		2	
	Cr.14	30.69	2.40		3	

	Cr.15	32.99	2.58		1	

Table.3.4. Results for Firm performance obtained through TOPSIS

Criteria	Weight	Ranking
Cr.16	14.46	5
Cr.17	12.60	6
Cr.18	15.15	4
Cr.19	20.30	2
Cr.20	16.29	3
Cr.21	21.20	1
Total	**100.00**	

3.8. Qualitative Analysis (Content Analysis):

In addition to quantitative analysis, qualitative analysis (content analysis) was also performed on the in-depth interviews conducted with all 8 respondents. Average time for the interview was 52 minutes. During in-depth interviews, CTOs were asked semi-structured questions within the framework of criteria used for data collection for quantitative analysis. The CTOs were also asked the challenges in creating a data-driven decision-making business environment and for their recommendations to cope with those challenges. The CTOs were also asked to share their experience during this technological transformation and perception of top management regarding this technological transformation. Content analysis was performed to abridge the responses and derive useful insights. A comparison was made between the results of content analysis and results obtained from quantitative analysis for the sake of validity of results.

The content analysis reveals that:

i. Top management's lack of knowledge of IT developments makes CTOs job difficult.
ii. Information systems within-firm are integrated among departments but stakeholders are not integrated into the system.

iii. Since all the firms included this study were involved in exports and have an international orientation. Dealing with large-scale international companies is a drive to modify their operations in response to technological advancements.

iv. The firms involved in large-scale manufacturing have been more adaptive to data-driven culture than smaller ones.

v. Firms do not have an independent data analytics department, At present, data analysis is being done within IT departments. The possible explanation is the lack of standardized education in IT and data analysis.

vi. Reducing cost and waste makes a big difference in profitability for manufacturing firms. So, Manufacturing firms are more likely to develop an absolute data-driven business infrastructure integrated amongst all stakeholders.

vii. There is the dire need of standardized IT education in the country like education of medicine, engineering, and chartered accountancy is standardized.

viii. There is a provincial level association of CTOs. All CTOs meet regularly to discuss the advancements in the field of IT and IS and share their experiences and thoughts. The purpose of these meetings is to introduce and adopt the updated software and programs and benefit from other's experiences.

ix. There is a general misconception in the market of taking IT/IS departments as expenditure departments not as an investment that is the reason lack of interest in investing in IT/IS assets by the investors.

3.9. Ethical Considerations

Before administering the questionnaire, the formal permission from the Research Ethics Committee of the university was obtained and communicated to the participants. The contribution of the participants was voluntary and no coercion of any kind was implied. The participants were contacted personally on their personal contact information and were briefed about the purpose of this study and explanation of the questionnaire. They were notified that they can decline to be participants if deemed not fit regardless of the consequence of any kind. The participants were ensured to keep their names, association with the firm, contact information, and other personal information of any kind confidential and will not be revealed at any stage of this study.

CHAPTER 4

DISCUSSION AND CONCLUSION

This chapter presents the discussion on the results obtained through both quantitative and qualitative data analysis and then linking the results of both analyses to reach a conclusion.

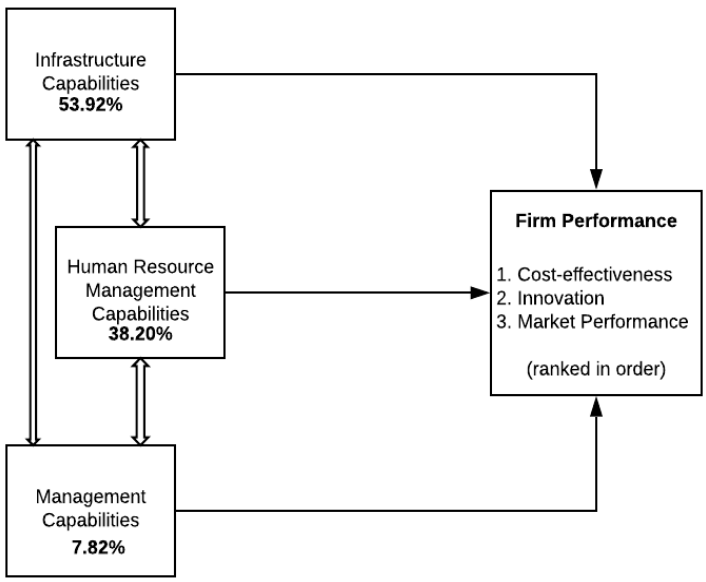

Fig. 4.1. Full research model

4.1. Discussion of results obtained through quantitative analysis

Each cluster of each BDAC consists of 5 criteria. This highest ranked "infrastructure capability" consists of 5 criteria. The analysis ranked the "capacity of IS infrastructure to handle multiple applications" the highest, followed by the "quick response to requests from internal and external customers", "strong infrastructure across organizational units", "flexibility of the infrastructure to develop customized software application in case of need", and "fast and flexible operations for internet-based system" respectively. The two highest-ranked criteria are directly related to the speed and performance of an information system including software and hardware.

The ANP ranked "knowledge of IS staff about computer-based system" as the most important criteria with the cluster of second most important BDAC i.e. HR capabilities followed by "quick maintenance of system failure", "early detection of potential problems in system", "right application at right time", and "seeking high degree of computer-based technical expertise of IS staff". Based on the relative importance, high level of expertise of IS staff absolutely essential and the participant firms have well-established IS department and Qualified staff.

In the cluster of third-ranked capability i.e. management capability, the most important criteria ranked is "clear guidelines to IS staff about IT resources" followed by "well defined and well documented IS processes", the executive-level authority of IS managers, and "IS strategy in line with corporate strategy". The management capability is ranked the lowest and the link between corporate strategy and IS strategy is very week. That depicts the lack of prioritizing IS strategy by top management.

TOPSIS results ranked the "Return on sales" the highest followed by "cost-saving", "number of new products and services projects", "product development", "market share", and "sales growth" respectively. The criteria for measurement of firm performance can be further classified into three categories; First and the highest-ranked category "cost-effectiveness" that includes cost-saving" and "return on sales" indicates that BDAC brings operational efficiency. Moreover, the expenditure made on building information system is an investment that benefit is higher than the cost. The second-highest ranked category "innovation" consists of "number of new product development and service projects" and "product development" is an indication of building firm's capability to innovate its product, services, and operations by building BDAC. The last category "Market performance" that includes "sales growth" and "market share" ranked the lowest. BDAC has a slow and gradual impact on market performance, marketing or sales performance because BDAC is more of internal capacity building and development.

4.2. Discussion of results obtained through qualitative analysis

Based on the content analysis of responses obtained through semi-structured interviews with the participants, in the last decade, most of the firms upgraded their IT and IS infrastructure to technological advancement. In a traditional business environment, up-gradation is more challenging.

The existing BDAC literature highlights the moderating effect of building on data-driven culture in business firms and evidence-based decision making on firm performance. This study applied a different approach and explored that infrastructure capabilities are the most important capabilities amongst other BDAC and have the most effect on firm performance. This corroborated the findings of the existing literature. This study further explored the relative importance of certain capabilities within three BDAC.

4.3. Conclusion

The quantitative and qualitative analysis reveals that the firms are working on developing their big data analytics capabilities yet those firms need to prioritize in developing a culture of evidence-based decision-making. The top management needs to prioritize the utilization of data and develop big data analytics capability for the firms to keep up with the recent trend in the market and gain competitive advantage by developing data-driven decision-making.

4.4. Managerial Implications

This study gives a picture to the senior management how developing big data analytics capabilities is contributing towards firm performance and it also identifies the areas where firms need to focus more to maximize utility out of big data. Pakistan is among those countries that are on their way to develop technologically advanced business environment yet they have a long way to go. This study explored the big data analytics capabilities of the firms operating on the traditional business model and are transforming to technologically advanced operation. The sample firms are investing both financially and non-financially to build big data analytics capabilities. This study highlights and ranks the capabilities and their relative effect on firm performance so that top management can devise strategies based on their strengths and weaknesses. Firms can increase their operational efficiency by developing an integrated IS and IT system with their stakeholders.

4.5. Limitations and further recommendations

Albeit the findings of this research contribute to the big data literature by applying MCDM techniques, it has certain limitations. Since the sample is limited to one city, the results obtained through the sample impede the generalizability of results. Further research can be done with a larger sample set and by extending the geographical boundaries. Either by including other cities of Pakistan or by enlarging the sample across boundaries for instance including other countries. Further studies can be conducted by applying different MCDM methods. Moreover, further research by including more capabilities or by examining external factors that influence developing big data analytics capabilities can also be explored.

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APPENDICES

Appendix.A. The distinction between Data, Information, and Knowledge

Data	**Information**	**Knowledge**
“Unprocessed raw representation of reality” (Faucher et al., 2008)	“Data that has been processed in some meaningful way” (Faucher et al., 2008)	“Information that has been processed in some meaningful way” (Faucher et al., 2008)
“Discrete, objective facts about events” (T. H. Davenport & Prusak, 1998)	“Data that makes a difference” (T. H. Davenport & Prusak, 1998) (King, 2008)	“A fluid mix of framed experiences, values, contextual information, and expert insight that provided a framework for evaluating and incorporating new experiences and information” (T. H. Davenport & Prusak, 1998)
“Symbols that represent the properties of objects and events” (Ackoff, 1989)	“Data that is processed to be useful” (Ackoff, 1989)	“Knowledge answers the how-to questions and conveys instructions” (Ackoff, 1989)
	“A result of analyzing and interpreting data that carry meaning” (Bourdreau & Couillard, 1999)	“A set of insights, experiences, procedures considered authentic and drive people to take effective actions” (Bourdreau & Couillard, 1999)
	“Data that has relevance, purpose, and context” (Smith, 2001)	“A human, highly personal asset representing the collective expertise and efforts of networks and coalitions” (Smith, 2001)
	“Data organized to characterize a particular situation, condition, context, challenge, or opportunity” (Wiig, 2011)	“Facts, perspectives, and concepts, mental reference models, truths and beliefs, judgments and expectations, methodologies, know-how to create new meanings of information” (Wiig, 2011)

	"Data with special relevance and purpose" (Drucker, 1995)	"Information whose validity has been established through sets of proof" (Liedbeskind, 1996)
	"The result of human interpretation of data" (Lueg, 2001)	"Authenticated and true to be social actions" (Stacey, 1996)
	"Structured data that supports decision-making" (Laihonen, 2006)	"Justifies personal belief that is held to be true and drive people to action justifies the personal belief that increases an individual's capacity to take effective action" (Alavi & Leidner, 1999)

Appendix.B. Definitions of Analytics/Business Analytics
(Delen & Zolbanin, 2018)

Definition of Analytics/Business Analytics	Dynamo	Reference
"Exploration and analysis of data to produce results that are actionable and measurable."	Business dilemmas	(Kohavi, Rothleder, & Simoudis, 2002)
"Collection, storage, analysis, exploration, and interpretation of volumes of data to make decisions and act accordingly"	Effective decisions	(T. H. Davenport, 2006)
"The extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions. Analytics is a subset of business intelligence."	Effective decisions	(Turel & Kapoor, 2016)
"A process of converting data into action through analysis and insights with the aim of problem-solving and decision making in an organization."	Data, Process, People, Software	(Liberatore & Luo, 2010)
"Interpretation of organizational data to improve decision-making and to optimize business processes."	Organizational data	(Shanks, Seddon, Reynolds, Shanks, & Seddon, 2010)
"The scientific process of transforming data into insight for making better decisions."	Booming data	(INFORMS, 2012)
"The process of developing actionable decisions or recommendations for action-based upon insights generated from historical data."	Archival data	(Sharda, Asamoah, & Natraj, 2013)
"Analytics facilities realization of business objectives through reporting of data to analyze trends, creating predictive models to forecast future problems and opportunities and analyzing/optimizing business processes to enhance business performance."	Data	(Delen & Demirkan, 2013)
"Evidence-based problem identification and solution and context of business situations."	Data	(Holsapple, Lee-Post, & Pakath, 2014)
"Data acquisition, storage, retrieval, and analysis to gain efficient and effective insights for decision making."	Data	(Turel & Kapoor, 2016)

Appendix.C. Taxonomy of big data analytics capabilities

Relevant studies	Infrastructure capability	Human resource capability	Management capability
(Kiron, Prentice, & Ferguson, 2014)	Organizational openness, compatibility analytics technology, collaborative use of technology	Analytical talent, technical and business knowledge, organization's effectiveness in disseminating insights	Analytics planning, sharing and coordinating, investment, control on analytics as a whole
(T. H. Davenport & Patil, 2012)	Connectivity, compatibility, and modularity	Data scientist	Analytics management at core businesses and operational functions
(Brynjolfsson & McAfee, 2012)	IT infrastructure	Skills and knowledge of data scientist	Corporate strategy
(Wixom, Yen, & Relich, 2013)	Data, BA tools	IT team	IT Strategy
(Barton & Court, 2012)	Data and IT platform	People	Managers
(Fosso Wamba et al., 2015)	Connectivity, compatibility, and modularity	Management	Management, technical and business relations
(Ransbotham, Kiron, & Prentice, 2015)	Infrastructure and processes	Managerial decision making	Technical knowledge and skills

Appendix.D. Perspectives of competitive advantage in strategic management

Study	Capabilities construct	Dependent variable	Theoretical Framework	Dimensions of IT and related capabilities
(Ross, Beath, & Goodhue, 1995)	IT capability	Long-term competitivenes s	Resource-based view	Three critical IT assets: Human Resource, reusable IT infrastructure, the relationship between IT and business management.
(Wade & Hulland, 2004)	IS resources		Resource-based view	External relationship management, Market responsiveness, IS-business partnership, IS planning and change management, IS infrastructure, IS technical skills, IS development, cost-effective IS operations
(Tippins & Sohi, 2003)	IT competency	Firm performance	Resource-based view	IT knowledge, IT operations, IT objects
(Duncan, 1995)	IT infrastructure flexibility		Resource-based view	Infrastructure technology components, flexibility characteristics,
(Lewis & Byrd, 2003)	IT infrastructure			Chief information officer, IT planning, IT security, technology integration, advisory committee, enterprise model, data administration
(Bharadawaj, 2000)	IT capability	Firm performance	Resource-based view	IT infrastructure, human IT resources, IT enables intangibles
(Ray, Muhanna, & Barney, 2005)	IT resources and capabilities	Performance of the customer service process	Resource-based view	Technical IT skills, generic IT, IT spending, shared knowledge, flexible IT infrastructure, IT complementarities

(Ravichandran & Lertwongsatien, 2005)	IS capabilities	Firm performance	Resource-based view	IS planning sophistication, systems development capabilities, IS support maturity, IS operations capability
(Bhatt & Grover, 2005)	IT capabilities	Competitive advantage	Resource-based view	IT infrastructure quality, IT business experience, relationship infrastructure
(Aydiner, Tatoglu, Bayraktar, Zaim, & Delen, 2019)	Adoption of business analytics	Firm performance	Resource-based view	Data acquisition and processing, Prescriptive analytics, predictive analytics, descriptive analytics
(Bronzo et al., 2013)	Business analytics	Firm Performance	Dynamic capabilities	
(Akter et al., 2016)	Big data analytics capability	Firm performance	Resource-based view, Socio-materialism	Big data management capability, big data technology capability, big data talent capability
(Cao, Duan, & Li, 2015)	Business analytics	Decision-making effectiveness	Information processing view, contingency theory	Data-driven environment, information processing capability
(Mithas, Ramasubbu, & Sambamurthy, 2011)	Information management capability	Firm performance	Resource-based view	Performance management capability, customer management capability, process management capability
(S. P. Wu, Straub, & Liang, 2015)	IT governance mechanism and strategic alignment influence	Organizational performance	Resource-based view	Decision-making structure, formal process, communication approach, product strategic alignment, quality strategic alignment, market strategic alignment
(Santhanam &	Information technology capability	Firm performance	Resource-based view	Profit ratios, cost ratios

Hartono, 2003)				
(Vidgen, Shaw, & Grant, 2017)	Business analytics capability	Value creation	Resource-based view	Technology, Organization, Process, people
(Kim, Gimun, Bongsik Shin, Kyung Kyu Kim, 2011)	Information Technology capabilities	Firm performance	Dynamic Capabilities	IT management capabilities, IT personnel capabilities
(Gold, Malhotra, & Segars, 2001)	Data-driven decision making	Firm Performance	Information processing view	Business Practices, information technology investments
(Gold et al., 2001)	Knowledge management capabilities	Organizational effectiveness	Knowledge-based view	Knowledge infrastructure capability, knowledge process capability
(Fink & Neumann, 2007)	IT personnel capabilities	IT-independent organizational agility		Business capability, behavioral capability, technical capability
(Wang et al., 2019)	Big Data Analytics	Quality of Care in Healthcare organizations	Resource-based view/Configuration theory	Primary capabilities such as analytical personal skills, data integration, analytical, predictive, data interpretation capabilities and complementary organizational resources such as evidence-based decision making, data governance, improvisational and planned dynamic capabilities.
(Akhtar et al., 2019)	Big data-savvy teams' skills and action	Business Performance	Resource-based view, Human Capital Theory	Multi-disciplinary skills and data-driven insights of the big data-savvy teams

(Mikalef et al., 2019)	Big data analytics capabilities	Innovation	Resource-based view, Resource Orchestration Theory	Tangible (Basic resource and data), Human Skills (Technical and managerial skills) and Intangible (Organizational learning and data-driven culture)
(Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019)	Big data and predictive analytics	Manufacturing performance	Resource-based view, Institutional Theory, and Big data culture	Tangible resources (Data connectivity, technology, basic resources) and Human skills.

Appendix.E. An overview of Multi-criteria decision-making methods
(Velasquez & Hester, 2013)

Methods	Definition	Areas of Application
Multi-attribute utility theory (MAUT)	"An expected utility theory that takes uncertainty into account and assigns utility to all possible consequences and outlines the best course of action."	Economics, Finance, actuarial sciences, agriculture, water, and energy management
Analytical hierarchy process (AHP)	"A user-friendly, scalable; paired comparison method that gives the hierarchical structure of alternatives."	Political strategy and planning, public policy, corporate policy and strategy, resource management, performance-related problems
Analytical network process (ANP)	"A generalized form of AHP that develops network structure and can better handle interdependence than AHP."	Project selection, product planning, green supply chain management, and optimal scheduling problem
Fuzzy set theory	"Fuzzy logic embraces vagueness and deals with imprecise and uncertain input. Considers the insufficient information."	Economics, environment, engineering, medical and social problems
Case-based reasoning (CBR)	"Proposes the possible solution to problems based on cased of similar nature and can improve over time."	Medicine, vehicle insurance, businesses, and engineering design
Data envelopment analysis (DEA)	"A linear programming technique that analyzes and quantifies the efficiencies of decision-making units against each other and against the benchmark. It can handle multiple inputs and outputs."	Medicine, utilities, road safety, agriculture, retail, economics, and business problems
Simple multi-attribute rating technique (SMART)	"The simplest form of MAUT and able to convert weights into actual numbers."	Transportation and logistics, construction, environment, engineering, military, manufacturing, and assembly
Goal programming (GP)	"Programming method that can handle large-scale problems and chooses from the countless number of alternatives."	Wildlife management, energy planning, water reservoir management, scheduling, production planning, scheduling, healthcare, portfolio

		selection, and distribution systems
ELECTRE	“An outranking method that is based on concordance analysis and considers uncertainty.”	Economics, energy, transportation, environment, and water management
PROMETHEE	“A user-friendly outranking method that does not require the assumption that the criteria are proportionate.”	Hydrology, water management, agriculture, energy, logistics and transportation, chemistry, business and finance, manufacturing, and assembly
Simple additive weighting (SAW)	“A value function that involves the simple addition of scores and multiplied by weights. It can compensate among criteria and very intuitive to decision-makers.”	Water management, business, and financial management
The technique for order preferences by similarity to ideal solutions (TOPSIS)	“Detects an alternative that is closest to the ideal positive solution and farthest from an ideal negative solution.”	Human resources, water resource management, business and marketing, engineering, supply chain management, logistics, and environmental

Appendix.F. The most cited studies using ANP

Author	Title
(Sarkis, 1998)	“Evaluating environmentally conscious business practices”
(L.M. Meade & Sarkis, 1999)	“Analyzing organizational project alternatives for agile manufacturing processes: an analytical network approach”
(Lee & Kim, 2000)	“Using the analytic network process and goal programming for interdependent information system project selection”
(Laura M. Meade & Presley, 2002)	“R&D project selection using the analytic network process”
(Sarkis, 2003)	“A strategic decision framework for green supply chain management”
(Karsak, Sozer, & Alptekin, 2002)	“Product planning in quality function deployment using a combined analytic network process and goal programming approach”
(Ravi, Shankar, & Tiwari, 2005)	“Analyzing alternatives in reverse logistics for end-of-life computers: ANP and balanced scorecard approach”
(Chung, Lee, & Pearn, 2005)	“Analytical network process (ANP) approach for mix planning in semiconductor fabricator”
(Kahraman, Ertay, & Büyüközkan, 2004)	“A fuzzy optimization model for QFD planning process using an analytical network approach”
(Shyur & Shih, 2006)	“A hybrid MCDM model for strategic vendor selection”
(Agarwal, Shankar, & Tiwari, 2006)	“Modeling the metrics of the lean, agile and leagile supply chain: An ANP-based approach”
(Jharkharia & Shankar, 2007)	“Selection of logistics service provider: An analytic network process (ANP) approach”
(Liou, Tzeng, & Chang, 2007)	“Airline safety measurement using a hybrid model”
(Yüksel & Dağdeviren, 2007)	“Using the analytical network process (ANP) in a SWOT analysis-A case study for a textile firm”
(Gencer & Gürpinar, 2007)	“Analytics network process in supplier selection: A case study in an electronics firm”
(W. W. Wu, 2008)	“Choosing knowledge management strategies by using a combined ANP and DEMATEL approach”
(Demirtas & Üstün, 2008)	“An integrated multi-objective decision-making process for supplier selection and order collection”
(Kuo, Wang, & Tien, 2010)	“Integration of artificial neural network and MADA methods for green supplier selection”
(Büyüközkan & Çifçi, 2012)	“A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS to evaluate green suppliers”
(Brandenburg, Govindan, Sarkis, & Seuring, 2014)	“Quantitative models for sustainable supply chain management: developments and directions”

Appendix.G. Measurement Scale

Section-1- Big data analytics capabilities

A- Infrastructure Capabilities	
Cr 1	Our IS infrastructure is strong enough between inter-organizational units (Aydiner et al., 2019).
Cr 2	Our IS infrastructure is suitable for developing customized software applications when the need arises (Aydiner et al., 2019).
Cr 3	Our IS infrastructure can respond quickly to requests from internal and external customers (Aydiner et al., 2019).
Cr 4	Our IS infrastructure capacity can handle multiple applications (Aydiner et al., 2019).
Cr 5	Our IS infrastructure provides fast and flexible operations for the internet-based system (Aydiner et al., 2019).

B-Human Resource Capabilities

Cr 6	Our IS staff has adequate knowledge of the computer-based system (Aydiner et al., 2019).
Cr 7	Our firm seeks a high degree of computer-based technical expertise for the IS department's employees (Aydiner et al., 2019).
Cr 8	Our IS staff is capable of implementing the right application at the right time (Ravichandran & Lertwongsatien, 2005).
Cr 9	Our IS staff is capable of discovering potential problems rapidly in the system (Aydiner et al., 2019).
Cr 10	Our IS staff is capable of quickly maintaining the system whenever a failure occurs (Aydiner et al., 2019).

C-Management Capabilities

Cr 11	Our firm's IS strategy is in line with our corporate strategy (Aydiner et al., 2019).
Cr 12	Our firm's IS managers have an executive-level authority (Aydiner et al., 2019).
Cr 13	Our IS processes are well defined and documented (Aydiner et al., 2019).
Cr 14	Our IS department has a clear guideline on how to prioritize service requests from users (Aydiner et al., 2019).
Cr 15	Our IS department has a clear guideline on how to use IT resources in our firm (Aydiner et al., 2019).

Section-2- Firm Performance

Cr 16	Market share (Ravichandran & Lertwongsatien, 2005) (Aydiner et al., 2019).
Cr 17	Sales growth (Ravichandran & Lertwongsatien, 2005) (Aydiner et al., 2019).
Cr 18	Product development (Aydiner et al., 2019).
Cr 19	Cost-saving (Ravichandran & Lertwongsatien, 2005) (Aydiner et al., 2019).
Cr 20	A number of new product and service projects introduced (Aydiner et al., 2019).
Cr 21	Return on sales (profit/total sales) (Aydiner et al., 2019).