CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

Impact of Big Data Analytics Competency on Firm Performance with Mediating Role of Decision Making Performance and Innovation Capability

by

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A thesis submitted in partial fulfillment for the degree of Master of Science

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Dedicated to my grandfather Sheikh Muhammad Akram

CAPITAL UNIVERSITY OF SCIENCE & TECHNOLOGY
ISLAMABAD

CERTIFICATE OF APPROVAL

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Abstract

Big data analytics is emerging as a game changing capability which generates valuable insights and reveals new patterns to keep organizations up-to-date and plan their moves accordingly. This research study aims at exploring the contribution of big data analytics competency in improved firm performance and those underlying resource dimensions which drives the high level of BDAC. Based on estimated population of both the sectors, Cochran formula has been used to calculate the sample size for current research. Empirical results obtained through quantitative analysis of data collected from 300 employees of such firms which are practicing big data analytics in their units; specifically of telecommunication and banking corporations across Pakistan identified that performance of a firm significantly increases when high level of big data analytics competency is developed and that the decision making performance and innovation capability mediates this relationship. In addition, findings of the current study demonstrate that big data analytics competency of a firm makes a positive and significant contribution in its decision making performance such that higher level of former-mentioned variable (i.e. BDAC) will results in improved performance of later one (i.e. DMP). The study therefore, significantly contributes to the domain of big data analytics management and organization performance and draws the attention of researchers as well as practitioners to consider the behavior of decision making performance and innovation capability in this association while suggesting the potential for future researchers to explore this relationship with possible moderators like top management support, employees commitment or readiness for change.

Keywords: Big Data Analytics Competency (BDAC), Decision Making Performance (DMP), Innovation Capability (IC), Firm Performance (FP).

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Abbreviations

BDA	Big Data Analytics
BDAC	Big Data Analytics Competency
DMP	Decision Making Performance
FP	Firm Performance
H	Hypothesis
HGD	Human Generated Data
IC	Innovation Capability
IDC	International Data Corporation
IT	Information Technology
IWS	Internet World Stats
JSON	JavaScript Object Notion
MGD	Machine Generated Data
OECD	Organization for Economic Corporation and Development
RBT	Resource Based Theory
RO	Research Objective
RQ	Research Questions
XML	Extensible Markup Language

Chapter 1

Introduction

1.1 Background of the Study

In this presently digitized era, an immense increase has been observed in the volume of user-generated data owing to explosive growth in number of internet and social media users (Verma et al., 2018). According to 2018 IWS report (Internet World Stats, 2018), over 4.15 billion internet users were recorded globally by the end of December 2017, which makes 54.4 percent of world population. Out of this marked population of internet users, 71 percent is reported as social networks user (Statista, 2018) and there is a strong indication of major escalation further. Thus, the rapidly increased usage of digital devices such as laptops, tablets, smart phones, smart watches etc. creates bulks of data every single day which eventually makes the data more complex and consequently led towards an era of ***"Big Data Analytics"*** (Bhimani & Willcocks, 2014).

Over last few years, big data has emerged as a prominent game-changing technological development (Dos Santos et al., 2014) and as a new "frontier" in the broad range of IT-driven innovations and information-enabled opportunities (Goes, 2014) with the competency of revolutionizing business as well as academic circle (H. Chen, Chiang, 2012). The notion of big data has been driven by the rapid rise in production and storage of data (Kacfah Emani et al., 2015) due to advancement in technology, internet, mobile machines, digital sensors, communications and computations (Bryant et al., 2008) such that datasets are too big in size and too fast in speed to be captured, handled and analyzed using existing traditional software tools (James Manyika et al., 2011).

In this era of digital devices, every single action taken around is transforming into some form of data. According to 2018 International Data Corporation IT predictions (IDC, 2018) "everyone will be a data-provider" by 2020. It was estimated that by 2018, there will be a transfer of 50,000 gigabytes of data every single second through internet. In addition, recent research has revealed that there will be creation of 43 trillion gigabytes of data by 2020 that is 44 zettabytes which is 300 folds of data generated by 2005 (IBM, 2013) and this number will reach to 160 zettabytes by 2025 (Reinsel et al., 2017). Adding more to it, Raguseo (2018) has identified that this increase in data is driven by various sources which are broadly classified as Machine-Generated Data and Human-Generated Data (Davenport, 2014); where machine-generated data accounts for the automatic creation of big data by digital machines such that direct human-enabled intervention is not involved (e.g. audio, video, image and speech data, sensors data, security cameras data, medical devices data etc.) while human-generated data involves creation of big data by direct interaction of humans with computers (e.g. social media posts-generated data, click-streams data, web content etc).

Big data is now believed as one of the fastest evolving future technologies and is considered different from traditional data not merely because of its distinctive nature of size and speed but due to five fundamental 'Vs' which makes it 'Big' in true context (Gupta & George, 2016). These 5Vs are volume, velocity, variety (Laney, 2001), value (Dijcks, 2013) and veracity (White, 2012). In the existing literature, it is however argued that out of these five, three of the Vs which are volume, velocity and variety are the primary whereas veracity and value are endogenic characteristics of big data (Lam et al., 2017). Referring to the most commonly adopted big data dimensional framework of 5Vs, the key element of this block which is ***volume*** highlights the size or quantity of generated data and the minimum size of data generation to be called as big data is 1 terabyte (Gandomi & Haider, 2015). Next to volume, comes the ***velocity*** which depicts the rate at which data is produced and processed; velocity of big data is high enough to refer it as near-real time creation (Ertemel, 2015). The third most significant element is ***variety*** which refers to the generation of different types of data via different sources and big data entails generation of three types of data through sources like humans and machines. These three types of data are: i) Structured data like numbers and dates, ii) Semi-structured data like XML and JSON files, and iii) Unstructured data like multimedia and social media content (Abbasi et al., 2016). ***Veracity*** being the fourth fundamental cube of 5Vs block, points the uncertainty and abnormality or imprecision and inconsistency of data. Veracity of big data indicates the level of consistency to which big data is precise and useful (Walker, 2012), driven by the belief that high extent of volume, velocity and variety increases big data veracity (Lam et al., 2017). Lastly, the most crucial element which completes the 5Vs block is ***value*** which delineates the usefulness of data. Big data is contemplated as data with high value (Joshi, 2015) as it provides an organization with economically worthy customers, market and competition related information subjective to its proper extraction such that it makes firm capable of improving decision making performance and developing real-time adaptations to their offerings (Lam et al., 2017). Thus, bigness of all the elements of big data is purposeless if it fails to add value to organization performance (Firican, 2017).

In today's age where the world has transformed into a digital globe and waves of big data have spread all around, firms in every sector are heavily flooded with data. These tides of big data can be brilliantly exploited to provide an extensively deep understanding of valuable insights, to improve productivity and achieve competitive edge over its peers using the right organizational resources and tools (Morabito, 2015). In addition, big data is grokked as a driving source for introducing innovative business products, services, models and opportunities (Davenport & Kudyba, 2016; Andrew McAfee & Brynjolfsson, 2012). However, underlying all this furtherance is decision making process of an organization. More than any other facet, big data enhances the firm decision-making performance (Maryam

Ghasemaghaei et al., 2018) as it enables an organization to get aware of internal and external information related to market, competitors, processes, employees, operations, products, regulations, prices (Song et al., 2018), unique consumers' needs and demands and many other significant factors which ultimately leads to improvement in decision quality and efficiency (E. Brynjolfsson et al., 2016). However, decision making culture and top management support plays a crucial role in this regard (Andrew McAfee & Brynjolfsson, 2012), as one of the underlying reasons of big data not being able to cause its potential impact is companies not taking the decisions based upon big-data extracted facts (J.W.Ross et al., 2013). Additionally , using merely the data in high volume cannot guarantee the effectiveness; the high quality and relevancy of data are the essential features to ensure betterment (Sukumar & Ferrell, 2013) of decision-making process. Likewise, the existing literature shows that analytical skills, domain knowledge (Waller & Fawcett, 2013) and analytical tools are some of the most vital factors which can nullify the beneficial impact of big data on firm performance, if not used properly and efficiently (Davenport, 2013). Organizations therefore, with the exponential growth of data are rushing to get them proficient big data analysts for validation and interpretation of data (Erevelles et al., 2016) and striving intensely to strengthen their big data analytics competency (Gupta & George, 2016).

In the present tumultuous environment of emerging economies and severe competition, organizations are moving rapidly towards adoption of most advanced and futuristic information technologies (Verma & Bhattacharyya, 2017). This thus, justifies the hype of "Big Data Analytics". BDA is widely acknowledged as a critical information-technology driven competency because of the vast pools of data available to organizations (Kambatla et al., 2014) such that it makes firms capable of running their businesses in the best possible way by driving efficient, facts-based and fast decisions (Maryam Ghasemaghaei et al., 2018); hence, providing better services to customers and making firms' operational and marketing performance higher. Indubitably, in near future the business competitions in reference to productivity and technologies will be BDA-driven (Philip Chen & Zhang, 2014). However, big data analytics appears with some challenges too in its infrastructure such as capturing, storing, managing, analyzing and visualizing data (H. Chen et al., 2012). But proper utilization and deployment of big data specified organizational resources and tools which makes big data analytics competency, can cater these issues properly (Maryam Ghasemaghaei et al., 2018).

Big data analytics add value to firm decision-making process by uncovering the previously hidden and unseen patterns and trends (Chong & Shi, 2015) which enable them to be a forward-looking and proactive entities (Wamba et al., 2017). In the existing literature, it is observed that BDA is posing its strong impact not only on a single industry but across number of various businesses. In travel and tourism, BDA is being used to makes predictions related to when, how and where people are interested in travelling and providing customers with services of their best possible interest (Y.-Y. Liu et al., 2018). In energy sector, it makes organizations capable of getting them aware with a minute-to-minute and an hour-to-hour energy demand and providing the right supply (G. Liu et al., 2018). In insurance businesses, this capability is beneficial to get them deeper picture of clients' risk history (Koutsomitropoulos & Kalou, 2017). In banking and finance industry big data analysis is advantageous to make businesses alert about rising opportunities and trading decisions (Tian et al., 2015). In agricultural field BDA is helpful in getting information related to crops prices, stock health, pesticides quantity and the demand of food (Pham & Stack, 2018). In health circle this competency is used to get familiarized with patients' history, health plans, trends in population etc. and provide right health at right time (Y. Wang & Hajli, 2017). In mining, big data is analyzed to get knowledge about raw material value and plan their logistics better (Perrons & McAuley, 2015). In education BDA provide teachers with a thorough insight about students, their academic history and progress so to act where needed (Li & Zhai, 2018). In telecom industry big data analytics help to know about customers' wants and needs related to services and packages and bringing them diversity to optimize network usage (Oghuma, 2013). In retail sector BDA is being used to alert them about demand and supply of stock by analyzing what, when and how customers are buying (Bradlow et al., 2017). In manufacturing industry it helps to predict about product demand and its production accordingly, to provide customers with better support and faster services and to understand the plant performance in different dimensions (Forbes, 2014). Hence, big data is everywhere and big data analytics is revolutionizing almost every sphere around.

The present research however, targets the telecommunication and banking industry of Pakistan and aims at analyzing the big data analytics competency and its influence on firm performance in terms of market and operational performance which is in line with the research study conducted by Gupta and George (2016); however, present study adds some more constructs to investigate the impact of BDA competency acutely. Besides, the present study suggests decision making performance and innovation capability as mediators in defined relationship.

1.2 Gap Analysis

In every domain of knowledge, some missing elements are always present which drives the future research and needs to be investigated. Number of gaps can be deduced from the already existed studies. A study by Gupta & George (2016) on development of big data analytics competency stated that it is yet an evolving domain and a number of possible resource dimensions can be included to analyze the more delineated impact of BDAC on firm performance. This therefore, provides the basis for first research gap. In compliance to big data specified resource dimensions which have been examined in the referred study (Gupta & George, 2016), the current research study adds some more constructs such as data quality, bigness of data and domain knowledge (Maryam Ghasemaghaei et al., 2018) in combination with types of data used, technology adopted, commitment to basic resources, proficiency of technical and managerial skills and development of data-driven culture (Gupta & George, 2016). No previous literature has been identified which incorporated all these nine dimensions simultaneously to explore the influence of big data analytics competency.

Next, it is observed that previous literature mainly analyzed the direct effect of big data analytics competency generated on firm performance (Collymore et al., 2017; Gupta & George, 2016; Song et al., 2018) or the direct effect of big data analytics competency generated on organization decision making performance (Banica & Hagiu, 2016; M. Ghasemaghaei et al., 2018). However, it is argued that big data analytics improve business performance directly as well as indirectly through decision-making and that a research study investigated the effect of BDA on business performance with moderating behavior of decision making performance has shown positive result (Thirathon et al., 2017). However, previous literature have revealed that role of organization decision making performance with respect to its quality and efficiency has also been examined as a mediator in various studies to investigate the firm performance (Carmeli et al., 2009; Nuhu & Bin Ahmad, 2017). This thus, drives the motivation to investigate the mediating role of decision making performance in relationship between big data analytics competency (independent variable) and firm performance (dependent variable).

Furthermore, existed literature in domain of big data analytics has revealed that researchers have tried to inquire the contribution of big data analytics competency in firm performance with number of mediating factors like operational performance (Garmaki et al., 2016), market performance, customer satisfaction (Raguseo & Vitari, 2018), dynamic capabilities (Wamba et al., 2017) etc. Moving in line with dynamic capabilities, past studies claim that dynamic capabilities and innovation capabilities of a firm, both offers a significant role and common characteristics (Breznik & D. Hisrich, 2014) in bringing innovation and enhancing firm performance which is among the primary objectives of big data analytics. This therefore leads the interest of current research study to be more specific and analyze the mediating behavior of innovation capability in association between BDAC and its influence on firm performance. Though, the mediating impact of innovation capability has already got examined in different studies to analyze the firm performance (Gebremichael & Renyong, 2015; Naala et al., 2017; Yang, 2012); however, to assembled knowledge, there has been no evidence found in previous literature pertinent to examination of innovation capability as a mediator in this context;

this thus offers a gap for the current study to explore.

Unfortunately, extant literature review has pointed out that there is a major scarcity of big data analytics-based studies in contextual setting of Pakistan as far as management side is concerned. This pushes the interest of current study to cover this gap by taking the telecom and banking industry of Pakistan into account to explore the big data analytics competency and its influence on firm performance.

1.3 Research Problem

Big data analytics has been emerged as an advanced IT capability and businesses are yet moving towards adoption of its practices; this area therefore, offers many unexplored domains. Taking the organization resources and dimensions into consideration, researchers and practitioners are highly interested in analyzing the role of various elements in development of big data analytics competency. The current research has attempted to address this problem to some level by incorporating the numbers of possible data-specific resource dimensions in BDAC to analyze its impact on firm performance.

Furthermore, past research has revealed the fact that higher big data analytics competency results in higher firm performance; however, decision quality and efficiency is significant in this regard. This makes up for the problem that decision making performance either improved or deteriorate, poses influence on a relationship between BDAC and firm performance. In addition, as BDA is driver of innovation, so along with decision making performance, innovation capability also offers a major part in making an impression upon firm performance. Thus, the element of innovation capability is worth noticing in this regard as an organization can possibly have low or high innovation capability. However, in any case, innovation capability affects the defined relationship. Owing to mentioned facts, there exists a need to investigate the mediating relation of decision making performance and innovation capability in relation between BDA competency and firm performance which is still uncharted. Assuredly, there are other factors too which can pose a strong impact on this relationship; however, current study as of now is interested in exploring the mediating role of decision making performance and innovation capability only.

1.4 Research Questions

In an endeavor to cover the identified research gap, under mentioned research questions are designed in the selected area:

RQ1: Does big data analytics competency contribute significantly in high firm performance?

RQ2: Does big data analytics competency contribute significantly in high decision making performance?

RQ3: Does innovation capability contribute significantly in high firm performance?

RQ4: Does decision making performance mediate the relation between BDAC and firm performance?

RQ5: Does innovation capability mediate the relationship between BDAC and firm performance?

1.5 Research Objectives

Big data analytics have emerged as a critical organizational capability since the last two decades (Kambatla et al., 2014). A prominently grand number of firms are placing excessive emphasis on use of big data analytics globally to deal with heavy bulks of data they collect in order to bring advantage through different dimensions and intensify firm performance (Fernández et al., 2014; Loebbecke & Picot, 2015). While taking sky-rocketing significance of big data analytics into consideration, this study aims at exploration of following under mentioned objectives:

RO1: To extensively analyze the IT and managerial skills driven big data analytics competency.

RO2: To investigate the effect of BDAC on firm performance.

RO3: To investigate the effect of BDAC on firm decision making performance.

RO4: To investigate the relationship between innovation capability and firm performance.

RO5: To investigate the mediating effect of decision making performance in relation between BDAC and firm performance.

RO6: To investigate the mediating effect of innovation capability in relation between decision making performance and firm performance.

RO7: To empirically test and validate the propound relationships in contextual setting of Pakistan telecom and banking industry.

1.6 Significance of the Study

1.6.1 Theoretical Significance

The current research is of immense significance as the already existed literature on big data analytics in context of Pakistani industries is excessively rare. Pakistan is a country where investment in IT related competencies is low as compared to major developed countries (Kanwal, 2017). The current research study therefore, is carried out with a target to analyze big data analytics competency precisely in contextual setting of Pakistan. Furthermore, the contribution offered by present study is significant as previous literature laid their emphasis majorly upon influence of BDAC (independent variable) on firm performance (dependent variable) with a limited number of dimensions in it (Gupta & George, 2016) but this study facilitate the literature by analyzing the effect of innovation capability (mediating variable) and decision making performance (mediating variable) in relation between BDAC and organization performance while making an effort to cover a significant number of possible resource dimensions. Investigation of already mentioned relation that is between BDAC and firm performance with mediating effect of innovation capability and decision making performance can assist researchers and practitioners to pay attention towards an opinion that it's not merely the higher big data analytics competency which generates higher firm performance, there are other variables too which needs to be focused upon.

Present literature highlights that there exists a variable upon which firm performance is majorly dependent that is decision making performance. The enhanced quality and efficiency of decision making performance are among the key factors to drive improved firm performance. If such is the case that big data analytics competency of a firm is high but decision making performance is not improved (owing to any possible reason), the enhanced firm performance can be in doubt. In addition, the current literature emphasizes that innovation capability mediates the relationship between BDAC and organization performance. BDA is majorly seen as an organization's competency which targets at bringing innovation (M. Gorman, 2018). However, if big data analytics competency is high but the innovation related knowledge and capability is low, the improved firm performance can be questionable.

1.6.2 Practical Significance

The current study offers a significant contribution in practical implementation of big data analytics as it firstly provides an integrated IT and managerial view of BDAC related facets which will help to focus on every possible aspect to improve this competency of firms. Secondly, the present study is of practical significance to improve firm performance as it focuses not on big data analytics competency solely but also on decision making performance and innovation capability, which provides extensive contribution in escalation of any firm performance.

1.7 Supporting Theory

1.7.1 Resource Based Theory

Resource-Based Theory is the underpinning theory of current research study, which is one of the extensively renowned theories in business settings for describing, elaborating and anticipating the organizational relationships (J. B. Barney et al., 2011) with a belief that competition among firms arises when they have resources which are rare in nature, hard to imitate, valuable when exploit and are properly organized (J. Barney, 1991). Since the past decade, the use of this theory has been grown by 500 percent (Kozlenkova et al., 2014). The significance of RBT at such a high degree owes to the fact that it acknowledges an organization as a body driven by the integration of alike and unalike resources, which as a consequence helps it to gain competitive advantage (Palmatier et al., 2007). RBT is of primary importance for analyzing not only the theoretical as well as empirical relationship between firm resources and its performance (Gupta & George, 2016). Taking the main aim of current research study into account, that is to analyze the integration and deployment of various firm big data analytics specified resources and its impact on firm performance, the use of Resource-Based Theory seems precisely suitable. This is in line with the view that RBT is advantageous not merely for determining the strategic worth of organization resources but also highlights the explicit dependency of organization performance on its resources (Wade & Hulland, 2004).

In context of present study, big data analytics competency is a capability of organization driven by collection and integration of various tangible, intangible and human resources such as the nature of data, technology and basic resources; bigness of data, data quality and data-driven culture; technical skills, managerial skills and domain knowledge respectively. Following RBT, current study suggests that better the integration and exploitation of resources in development of big data analytics competency, higher will be the capability of a firm to achieve desired results i.e. better firm performance. Additionally, innovation capability which is acting as a mediator in current study, is another resources-based capability of a firm which holds critical role in firm performance (Sáenz et al., 2009). Innovation capability of a firm depends upon the effective utilization of resources in various dimensions such as environmental awareness, alliances, customer intelligence, experimentation, strategy and planning, manager attributes, HR and human capital, resource awareness and operations (Balan & Lindsay, 2010). This capability of an organization helps to cope with rapidly changing environment by generating new ways, thus playing its vital part in firm performance (Naala et al., 2017). Moreover, decision making performance of a firm which is also acting as a mediator in present study, is a resource driven dimension too, as resources are among the main means on which organizational decisions are dependent (Nemati et al., 2010). Given that, Resource-Based Theory takes all the dimensions being explored in this study into its circle of influence thus justifying its adoption in the current research.

1.8 Definition of Variables

1.8.1 Big Data Analytics Competency

"Big-Data Analytics Competency" is the firm's integration and deployment of its big data-specified resources to make it capable of conducting a methodical and action-oriented analysis of detailed data (Gupta & George, 2016).

1.8.2 Decision Making Performance

"Decision-Making Performance" has been defined in terms of decision efficiency and quality as the extent to which the decision-making process is expedited and productive, simultaneously the decision-made outcome is not compromised such that it is precise and errorless (Jarupathirun & Zahedi, 2007).

1.8.3 Innovation Capability

"Innovation Capability" is the competency of an organization to persistently blend the knowledge and new ideas to introduce novel products and processes, systems and strategies; such that it can make a potent response to present and anticipated market and environmental challenges (Lawson & Samson, 2001).

1.8.4 Firm Performance

"Firm Performance" is a multi-dimensional concept (Miller et al., 2013). It is defined as a comparison level among firms on which they perform higher than their competitor (Rai et al., 2006).

Operational performance and market performance has been acknowledged as two main facets of firm's performance measurement where market performance refers to the level a firm exploits its resources to enter new markets and introduces new products and services to the market while the level to which a firm exploits its resources to enhance productivity, profitability and financial performance relative to its competitor indicates the operational performance of firm (Ravichandran and Lertwongsatien, 2005).

Chapter 2

Literature Review

The present study investigates the area of big data analytics competency, its underlying resource dimensions and its contribution in firm performance with mediating role of decision making performance and innovation capability. Extensive literature has been reviewed in the selected domain to analyze the already present studies and identify the gap. In addition, this chapter provides the conceptual understanding of conceptual framework with hypothesis generation for the current study.

2.1 Big Data Analytics Competency

Organizations develop their competitive advantage through their effort of integration and deployment of firm resources thus building their capabilities. IS researchers have distinguished a number of firm resources which when assembled and exploit together, generate high IT competencies giving organizations an edge of competitive advantage over their competitors (Seddon, 2014; Tallon & Carroll, 2008; Watjatrakul, 2005). Alongside with effective use of IT competencies, managerial abilities to make the efficient coordination of multi-dimension activities have been identified as one of the differentiators in firm performance (Sambamurthy et al., 1995). Since the last two decades, big data analytics competency has been distinguished as one such IT competency of firm which makes a strong impact on its performance (Kambatla et al., 2014). Big data analytics helps in discovering new ways and opportunities by digging deeply the user-generated data such that it enhances the businesses performance in developing economies (Dubey et al., 2016). Accenture and General Electric reported that 87 percent of enterprises are of opinion that BDA will drive the redefinition of their associated industries' competitive landscape in less than upcoming three years. Furthermore, 89 percent of companies think that those who do not move towards the ratification of big data analytics in the upcoming recent years will be at risk of losing market share and market momentum. Hence, BDA is now believed as fuel of competitive growth (Columbus, 2014).

Big data analytics is believed and functioned as a multifaceted competency of an organization where how well all the dimensions and resources are coordinated and assembled determines its impact on performance since each element offers its unique role in the formation of this capability (Maryam Ghasemaghaei et al., 2018). As big data analytics is IT-driven domain, yet IT-specified resources alone are not enough to be profoundly benefited from big data, the effective managerial and organizational skills plays an equal part too in developing an unmatchable firm competency (Y. Wang & Hajli, 2017). A large number of organizations have adopted the practices of big data analytics however some are yet in their adoption phase; this drives the fact that area of big data analytics is still developing and researchers have suggested that more data specified resource domains are needed to explore to enhance big data analytics competency of firms (Gupta & George, 2016). Additionally, enterprises are required to take changing environment into account and keep on configuring their resources accordingly (Teece, 2014). However, in order to make these efforts possible firms are imperatively needed to keep them aware of changing environment, trends and hence the available resources to create effective capabilities in order to compete and survive.

Based on Resource Based Theory, existed IT capabilities related studies and big data relevant literature (Maryam Ghasemaghaei et al., 2018; Gupta & George, 2016), a number of big data specified resources have been encircled to analyze the BDAC of an organization. Following RBT, these resources are differentiated under three generic categories as: (i) Tangible Resources, (ii) Intangible Resources, and (iii) Human Resources. Tangible are those resource which can be considered as an asset, which can be bought or sold; Intangible are those resources which are not physical in nature such as knowledge-based resources while human resources include employees' trainings, skills, relationships, experiences etc. (Grant, 1996).

2.1.1 Tangible Resources

2.1.1.1 Data

Data is considered as one of the most important resources in firms across all industries. It has been claimed that data serves information as a raw material while information serves knowledge as a raw material thus data itself is unrefined and unfiltered information (Liew, 2007). Nowadays, organizations are not merely interested in their own specific structured data to take organizational decisions rather they try to gain each and every piece of information around irrespective of its structure, size or its speed at which it is produced (J. Manyika et al., 2011).

Five main sources of high-volume data generation are identified as (i) Public data, (ii) Private data, (iii) Data exhaust, (iv) Community data and (v) Self-quantification data (George et al., 2014). Public data are the data-sets which are owned by government and local communities and include information related to domains like transportation, healthcare, energy usage, climate change etc. Contrary to public data, private data are the data-sets which are collected and owned by firms and individuals while it cannot be accessed by public sources easily. Private data include information relevant to consumer transactions, mobile phone usage, RFID generated data etc (Pantelis & Aija, 2013). Next, data exhaust refers to the data-sets which are produced as a buy-product of individual's actions thus collected passively and adds value when merge with other sources of data to create new insights. One such example of data exhaust is log files generated by web browser (Oleary & Storey, 2017). Another source of data is community data which are data sets extracted from the unstructured data to identify the trends and patterns. Data generated through online community like Twitter about product review is one of the many examples of community data (George et al., 2014). Last type of data is self-quantification which are data sets produced by individuals' quantification of their personal behaviors and activities like data created from smart wrist bands about movements (Almalki et al., 2015).

Organizational data are however classified under two common categories as internal data and external data. First, internal data as the name suggests include the data related to firms specified internal operations like inventory updates, financial information, human resource related information etc. while external data, contrary to internal data, are the data gathered through external means such as e-commerce units, mobile phones, sensors etc. Firms which integrate their internal data with external data for decision making are more credible to achieve competitive advantage comparative to those who rely merely on internal data as integration of external and internal data can dig more insights and reveal novel perspectives thus makes a valuable impact on firm performance (Zhao et al., 2014).

2.1.1.2 Technology

In reference to the most widely used 3Vs dimensional framework of big data, the key characteristics of big data which makes it different from the traditional data are (i) Volume which highlights the size or quantity of generated data and the minimum size of data generation to be called as big data is 1 terabyte (Gandomi & Haider, 2015). (ii) Velocity which depicts the rate at which data is produced and processed; velocity of big data is high enough to refer it as near-real time creation (Ertemel, 2015) and (iii) Variety which refers to the generation of different types of data via different sources and big data entails generation of three types of data which are structured, unstructured and semi-structured through sources like humans and machines (Abbasi et al., 2016). These three elements act as a differentiator for big data from usual data and thus demands new technologies which are advance enough to handle the gigantism, diversity and fast generation and transfer of big data. Organizations rely on some sort of technology to store data and gain insights from them. Relational database management systems (RDBMS) is one of the popular examples of technologies used by firms to keep structured data like record of customer orders, employees record, financial records, inventory management records etc. (Gupta & George, 2016).

In addition, ETL (extract, transform and load) process is adopted to take the data out from disparate sources and position it in data warehouses or data marts to dig the insights. Data warehouse thus incorporates the organization-specific assembled data, extracted from different enterprise functions and are made in conformance to a standard structure. The data are then analyzed to extract key performance indicators. However, the mentioned strategy or approach is beneficial only if the organizations are to deal with structured type of data or the data which can be easily conformed to the standard structure. But the studies revealed that 80% of data owned by firms are in unstructured format (Gupta & George, 2016). This calls for adoption of new technologies to deal with big data of different types generated through different sources. Hadoop is one such example of novel technologies which can handle processing of distributed and unstructured data (Matthew Panzarino, 2015). With the emergence of big data, acquisition of new technologies has become critical for firms to store, process, analyze and gain insights from piles of data available to them (Kaisler et al., 2013). Technology has always played a crucial role in gaining competitive advantage and making an organization superior to its peers (Nicholas G. Carr, 2003). However, it is not an easy job for organizations to keep their proprietary technologies secret owing to factors like employees' mobility, informal meet-ups and discussions from different organizations, reverse engineering etc. (Mata et al., 1995).

2.1.1.3 Basic Resources

Alongside with data and advanced technologies, organizations are required to invest adequately in basic resources to develop their big data analytics competencies. Taking the uniqueness and novelty of big data and the apposite technologies, jobs and duties into consideration, majority of organizations are still on their way yet to make standard strategies and procedures in this domain. There exists therefore, a probability that organizations practicing big data analytics in their system may not achieve immediate desired results. Though what matters is firm pertinacity and determination to achieve their analytical goals thus by devoting sufficient resources. Past IS based studies argued finance and time as such tangible resources which plays a vital part in creating effective big data analytics competency of organization subjective to consistent devotion of a firm to make investment in these resources (Mata et al., 1995; Wixom & Watson, 2001).

2.1.2 Intangible Resources

2.1.2.1 Bigness of Data

Bigness of data points towards the immense increase in availability of data around which generates the need for data analytics (Lycett, 2013). Big data is called big due to its distinguishing features of high volume, high variety and high velocity (Laney, 2001). This notion of big data is supported by numerous past studies (Kwon & Sim, 2013; Raghupathi & Raghupathi, 2014). The increased production of digital content through enhanced adoption of smart devices is adding tons of volume to data every single day (Newell & Marabelli, 2015). An estimation was made in 2011 that data creation will be increased to 50 times by 2020 (Ertemel, 2015). Increase in volume is not devised by just a single type of data rather it includes different varieties such as structured data, semi structured data and unstructured data (Abbasi et al., 2016; Li & Zhai, 2018). Organizations by now are interested in their own specific internal as well as external data to deduce new trends and patterns which not only adds to the volume but variety of data too. The third most distinguished characteristic of big data is its velocity. Big data is created at speed near to real time. A claim is made that 100h of video had been uploaded on YouTube every single minute in 2015 (Ertemel, 2015), is an example of high velocity of big data. These three features thus collectively drive the bigness of data. However, few studies argued that beside these three Vs, there are some other dimensions of big data too such as value which refers to the high economic benefits extracted from big data (Dijcks, 2013; Fosso Wamba et al., 2015; Gantz & Reinsel, 2013) and veracity which points to the level to which big data is consistent, precise and useful (Fosso Wamba et al., 2015; White, 2012). Yet past literature suggests that volume, variety and velocity are the primary (D. Q. Chen et al., 2015; P Russom, 2011; Ward & Barker, 2013) while value and veracity are endogenic characteristics of big data. (Lam et al., 2017). Organizations can add high value to their performance by identifying hidden patterns revealed as a result of processing and analyzing big data which is near-real time data with high volume and variety (Fernández et al., 2014). This imperative role of bigness of data makes it a key dimension of big data analytics competency (Anandhi S. Bharadwaj, 2000).

2.1.2.2 Data Quality

Data quality is determined by its fit for the purposive use, its accuracy and reliability, level of details, completeness and number of other characteristics. A categorical framework is developed by R. Y. Wang & Strong (1996) to conceptualize the fundamental features of data quality. This framework is based on four main categories of data quality which are (i) Accessibility (ii) Intrinsic, (iii) Representational, and (iv) Contextual, along with their underlying dimensions. Taking these four categories in to consideration, accessibility deals with the ease of obtaining data. Next, intrinsic refers to instinctive objectivity and rigorousness of data irrespective of the context in which it is to be used. Contextual is concerned with the thoroughness, timeliness and aptness of data which depends upon the distinct task at hand. While last representational points toward the clear and consistent presentation of data which makes it easy to understand (R. Y. Wang & Strong, 1996).

Although the crucial part played by data quality in effective decision making and firm performance has been acknowledged yet some recent reports claim data quality as a main hurdle in developing high data analytics competency (Hazen et al., 2014). This owes to the fact that in present age of big data, organizations want to analyze more and more of acquired data. Though novel analytical tools and technologies are advance enough to spot the useful and valuable information from data (Philip Russom, 2008), quality of data to be used still has an impact on the results of data analytics (Lycett, 2013; Popovič et al., 2014). It is therefore recommended that organizations should make use of only high quality data to gain valuable insights and make effective decisions to enhance firm performance (Lycett, 2013). Considering the critical role of data quality, Anandhi S. Bharadwaj (2000) stated it as one of the key dimensions in big data analytics competency.

2.1.2.3 Data-Driven Culture

A number of different opinions exist when it comes to defining the notion of organizational culture. Existing literature shows that different management scholars have different understanding of organizational culture where some are of view that it circumscribes all the domains of an organization (Iivari & Huisman, 2007), other suggests it as a glair which ties an organization together (Dowling, 1993); thus, there is lack of consent in this concern (House et al., 2002). Past management based studies recognized organizational culture as one of the key sources of firm's sustained performance (Teece, 2015). In conformance, recent studies in the area of big data acknowledged that an organization's culture has a crucial part in success or failure of BDA initiatives and that the unproductivity of big data relevant projects is linked more to organization culture than to the data attributes and technology insufficiency (LaValle et al., 2011). In addition, it is avowed that organizational culture possess the ability to enhance an organization's competency to use big data analytics and gain high advantage (Ross et al., 2013).

With the advancement in research done in the stream of big data, a fact is stated that despite of collecting bulk of data, only few of the organizations have actually attained the desired benefit through big data analytics investment (Ross et al., 2013). The underlying reason identified for this cause is that although organizations have started practicing big data analytics in their units, yet when it comes to decision making these entities are still obliged to experience and instinct of their top executives (Andrew McAfee & Brynjolfsson, 2012). Whereas, to fully exploit the big data analytics, organizations are required to develop their organizational culture as a data-driven culture which refers to the data propelled elements such as establishment of decision development on data extracted insights rather than top executives' intuitions (Andrew McAfee & Brynjolfsson, 2012; Ross et al., 2013). All the endeavor a firm invests in collection of huge amount of data, adoption of advanced technologies, creation of employees' skills however, is futile if decisions are designation-driven and not data-driven (Andrew McAfee & Brynjolfsson, 2012). This justifies the data-driven culture as the most important dimension in big data analytics competency.

2.1.3 Human Resources

2.1.3.1 Technical Analytics Skills

Technical analytics skills entail the level of expertise employees own related to knowledge and usage of sophisticated technologies to treat big data. Proficiency in data cleansing and data extraction, machine learning, data analysis and programming paradigms are few of the technical skills to analyze big data (Davenport, Thomas, 2014; P Russom, 2011). Recent literature reported that considering the escalation of big data analytics and its usage in industries, educational institutions also took the initiative of such courses which can instill big data specified skills in individuals however, scarcity is still there (H. Chen et al., 2012). It was reported that there will be demand of around 140,000 – 190,000 big data analytics experts just in United States by 2018 (J. Manyika et al., 2011). Generally, technical skills like programming, database expertise, system analysis and design are not rare but considering the novelty of big data technology and its associated skills, organizations having employees with mastery skills as their asset are probably superior to their competitors (Mata et al., 1995). On contrary, analysts possessing not enough of technical analysis skills might consider procrastinating things causing wastage of time, resources, making blunders yet being unable to deal with problems being faced (Maryam Ghasemaghaei et al., 2015) and consequently generating no good impact on organization performance. This thus, legitimates the vital role of technical analytics skills in building competency and effecting firm performance.

2.1.3.2 Domain Knowledge

Besides employees' technical analytical skills, domain knowledge is another dimension which needs to be focused. Domain knowledge in combination with analytical skills makes employees proficient in effectual analysis of data and task performance (Draganidis & Mentzas, 2006). It is worthless to collect heaps of data without domain knowledge as it would add no value to firm's performance in such a case. It is observed that some organizations invest heavily in discovering new business insights from data yet a very little in development of employees' knowledge (Waller & Fawcett, 2013). In accordance to RBV, human knowledge is among the resources which are most difficult to imitate thus provides an organization with supremacy of competitive advantage (Peteraf, 1993). While, knowledge is a resource which can never be taken away yet with the development of modern technologies, there is always a need of exploring new domains and updating organizational goals and capabilities to sustain in an unpredictable business world (Teece, 2015).

In context of data analysis and integration, possession and application of domain knowledge to the analysis of interest is considered as a crucial factor as it demands a sound understanding of the facts and system, processes and procedures of the firm and industry. Holding enough of a domain knowledge makes analyst capable of recognizing the core strengths and weaknesses, threats and opportunities so to find effective business solutions to concerning problems (Sukumar & Ferrell, 2013) and causing a better impact on firm performance. Domain knowledge therefore, is considered as an important dimension in the development of big data analytics competency (Anandhi S. Bharadwaj, 2000; Maryam Ghasemaghaei et al., 2018).

2.1.3.3 Managerial Skills

While technical analytics skills have been considered as an important dimension of big data analytics competency, managerial skills possess the same significance too. Where organizations can polish the technical skills of their workforce by trainings and by recruiting new experts on one hand, on other hand managerial skills are developed and refined over period of time with experience in organization (Mata et al., 1995). Development of managerial skills demand well-built bond among workforce of the same or different units or departments (Anandhi S. Bharadwaj, 2000). This attribute of managers is believed to be deeply-seated in firm setting and considered as taken-for-granted which makes managers capable of getting their work managed and done effectively (Anandhi S. Bharadwaj, 2000; Mata et al., 1995).

Taking the domain of big data into consideration as an IT driven competency, it is impossible to exploit it to its full advantage without managerial skills. Data driven intelligence will be of minimal value to an organization if its managers are not capable enough to see the rays of future benefits obtained from newly data-digged insights. It is therefore of immense importance to organizations that their managers hold intense understanding of application of newly discovered values driven through data analysis to such areas which can generate maximum benefits to a firm. To make this possible, big data managers are required to have a deep knowledge about present and future needs of other business units, their partners and their customers (Mata et al., 1995). Managerial skills, is thus a domain which cannot be overlooked when organizational competencies are analyzed.

All these resource dimensions have been driven through extensive review of already present literature and are used in current study to explore the domain of big data analytics competency.

2.2 Firm Performance

Firm performance has remained a focused factor of investigation in business research since forever by researchers and practitioners in different context and settings (Miller et al., 2013). It is acknowledged as a multidimensional concept of comparison among organizations on which one performs higher than its competitor (Rai et al., 2006). Furthermore, firm is referred as an organization with value maximization as its core objective through exploitation of its resources. Value maximization however, is derived by all such strategic decisions which can soar the market value of a firm in longer run (Jensen, 2001). In addition, Rappaport

(2016) claimed value maximization as a strategic challenge in business environment and to compete successfully an organization must have to be ahead of its competitors at seizing opportunities and developing potential competitive advantage which will enable it to create value and enhance firm performance (Koller, 2016).

In today's hyper competitive business world, firms are in severe competition with each other for their success and survival (Akben-Selcuk, 2016). Performance measurement system being a key part of development of organization strategy allows firms to evaluate their achievement level in terms of their defined organizational objectives (Vélez-González et al., 2011). Firm performance is mostly determined based upon its financial performance by evaluating factors like efficiency or return on investment (ROI), return on equity (ROE) and profit scales such as return on sales (ROS), net profit margin, turnover etc. (Reijonen & Komppula, 2007; E. Walker & Brown, 2004). However, financial measure only are not enough to assess firm performance owing to its limitation, as a claim has been made that merely accounting driven financial measurements are sometimes not sufficient to evaluate firm performance (Ferreira et al., 2010; Vélez-González et al., 2011). Therefore, beside financial measurements some non-financial factors which determines firm performance includes sales growth, customer satisfaction, employees' growth, job satisfaction, social performance, environmental performance, innovation, goal achievement, market share etc. (E. Walker & Brown, 2004) should be explored too. The combination of financial measures along with non-financial measures in assessing firm performance will enable managers to make effective diagnosis of progress and develop realistic and actionable steps to drive firms' success and value in respective market and make decisions accordingly (Otley, 2001). Thus, different outcomes determine firm success related to firm performance in a certain market (E. Walker & Brown, 2004).

The current study however follows the Ravichandran and Lertwongsatien (2005) concept of analyzing firm performance which incorporates firm market performance and firm operational performance as two main dimensions.

2.2.1 Market Performance

Ravichandran and Lertwongsatien (2005) referred market performance as a successful achievement of a firm in making entrance to new markets and offering new products and services. This concept is further endorsed by Kasemsap (2015) who argued that innovation plays an imperative role in meeting customers' needs and increasing market performance of a firm, thus attaining stable success. Therefore, organizations should be careful towards accurately assessing their needs for organizational innovations so to make immediate and effective response to market requirements (Kasemsap, 2015). Additionally, based on these assessments and their competencies firms need to develop different strategies to enhance their market performance (Jayapal & Omar, 2017). Furthermore, the dependency of firm improved market performance on organizational innovation has also been defended by Tidd et al. (2007) who points out that organizations which works on bringing innovations to make their system and processes better and their products and services differentiated capture major market share, higher profitability and company's growth.

2.2.2 Operational Performance

Ravichandran and Lertwongsatien (2005) referred operational performance as achievement of a firm in terms of improved productivity, higher profitability and higher return on investment. Regardless of industry and sector, productivity and profitability are two main concerns of every organization around (Morris, 2009). Profitability has been recommended as a key criterion to assess firm performance as it determines the return a firm receives based on its investments (Jiang et al., 2006). In addition, a research study identified that productivity level of a firm has a major impact on firm profitability and that organizations with higher productivity level are more likely to achieve competitive advantage over their competitors with low productivity level, which in turn gains higher profitability thus reflects improved firm performance (Kim & Ployhart, 2014; Meyrick et al., 2004). Moreover, Jovanovic (1982) argued that firms with high productivity level compete to survive while those with low productivity level ultimately dies in market competition and exit. Thus, organizations need to focus on elements like employees training, development and execution of strategic plans, exploitation of technologies and other capabilities which are the main drivers of firm productivity and profitability (López-Cabarcos et al. , 2015).

2.2.3 Relationship between BDAC and Firm Performance

The current study aims at investing the effect of big data analytics competency on firm performance and the underlying theory of the study is Resource Based Theory (RBT). RBT is one of the mostly used theories in organizational settings which describes, elaborates and anticipates organizational relationships (J. B. Barney et al., 2011) and believes that competition among organizations develop based on resources which are rare in nature, hard to imitate, valuable when exploit and are properly organized (J. Barney, 1991). In addition, RBT not only determines the strategic value of firm resources but also highlights the clear dependency of firm performance on its resources (Wade & Hulland, 2004).

Since the early 1990s, a number of studies laid their focus on IT productivity paradox which denies the existence of positive relationship between investment in IT domain and firm productivity/performance. However over time, the said paradox resolved owing to several research studies conducted to realize that along with IT investment, numbers of other resources are needed to be focused upon in order to drive the true value through IT investment. It was that time when IT was considered as a winning weapon, while in the present digital world big data analytics has emerged as one of the competitive weapons which can earn competitive advantage to firms (Gupta & George, 2016). Big data analytics competency incorporates a number of multiple other competencies (resource domains) in it including human resources, managerial resources and IT resources, which require proper investment to produce its true value in form of improved firm performance. Realizing the increasing importance of big data analytics, number of academic researchers and practitioners have attempted to understand when and how BDA can enhance the worth of organization through competitive advantage (Agarwal & Dhar, 2014; Corte et al., 2014).

A claim has been made that firms which practice big data analytics in their operations has reported 5% improvement in their productivity and 6% improvement in profitability compared to their competitors (Barton & Court, 2012). The improvement in firm performance due to application of big data analytics is subjected to its role of providing firms with insights regarding the present and future hidden patterns, thus planning their strategy and decisions accordingly to optimize the outcomes (Lavalle et al., 2011) by encouraging innovation and value creation which ultimately drives improved firm performance (J. Manyika et al., 2011). Despite of so many evidences of value creation and improved firm performance through big data analytics, some business executives and chief information officers are reported to show indecisive attitude about making huge investments in BDA owing to unsatisfactory results being observed by themselves or in other firms (Woerner & Wixom, 2015). However, it is argued that disappointing results of big data analytics could be due to the negligence of firms toward vital conditions and requirements for generating insights from data while keeping their concern only with data characteristics like volume etc. (Wu et al., 2016). It has been revealed that just 27% of the firms achieved the expected results by using big data analytics (Colas et al., 2014).

Furthermore, a prominent number of organizations are yet in initial stage of learning and understanding how to create value through BDA and what are the required resources and capabilities to get maximum of the benefits (Garmaki et al., 2016). Thus taking the already mentioned facts and growing importance of BDA and its relationship with firm performance into consideration, the current study hypothesis the following:

H_1: Organization's competency of big data analytics has a positive and significant impact on firm performance.

Here, big data analytics competency is proposed as an independent variable in a positive relation with firm performance, a dependent variable. Though, the proposed relationship has already been studied in different contextual settings yet this combination of big-data specified resource facets is not explored previously.

2.3 Decision Making Performance

Moorhead & Griffin (2001) defined decision-making as a complex phenomenon of selecting between available alternatives, such that the possible consequences of every individual factor involved are assessed and the best course of action is picked to execute (Muindi, 2011). In addition, Jarupathirun and Zahedi (2007) has defined decision-making performance in terms of decision efficiency and quality as the degree to which the decision-making process is expedited and productive, simultaneously the decision-made outcome is not compromised assuring that it is precise and errorless.

In previous studies it has been stressed that decision-making is a core process in any organization and the quality and efficiency of decision making process reflects the potential of managers on one hand and on other hand makes an impact on employees and organizational performance (Leonard et al., 1999). This notion is also advocated by McGregor (2010), who mentioned quality and efficiency of decision-making as a primary determinant of an entity's success or failure such that right decisions create value while wrong decisions can make millions of pounds to be lost. Blenk et al. (2010) also emphasized on quality of decision-making in his study and claimed that decisions take longer duration of time than it actually should when it is processed by wrong individuals or teams or in the wrong part of firm, driven by wrong information and the consequences ultimately turned out to be worst. Taking the importance of decision-making into consideration, most top executives are of the opinion that it is something which comes naturally; however, some researchers argued that owing to advanced knowledge and technology in the present era, the quality and efficiency of decision-making can improve significantly (McGregor, 2010).

2.3.1 Relationship between BDAC and Decision Making Performance

Huber (1990) proposed in his theory that whenever an organization adopts new form of technology, this adoption drives the redesigning of decision making process of that specific body. Carlson et al. (1999) defended this argument of Huber in his study and stated that when an organization move towards acquisition of advanced technologies in its system, the organizational intelligence and decision-making ultimately got affected such that the efficiency of decision making process and quality of decision outcomes improves. Referring to Huber (1990), it has been pointed out that the effective and systematic application of information-technology generates such organizational intelligence which is highly précised, well-timed and intensely detailed with prompt identification of organizational opportunities and threats. Additionally, Lu (2011) argued in his study that such organizations which possesses high level of IT capabilities are better at making more accurate and well-timed decisions comparative to those with lower level of IT capabilities. Big data analytics has been distinguished as one of the IT competencies of firms to treat bulks of data they own and studies have revealed that data analytics specified resources, when integrated and deployed effectively can improve decision-making capability of an organization (Maryam Ghasemaghaei et al., 2018) by generating better, faster and more informed decisions (Fernández et al., 2014).

Data analytics have gain significant importance in recent years owing to the creation of valuable insights from big data available to business organizations thus influencing an organization's decision making performance positively (Ertemel, 2015). Taking the growing influence of big data analytics into consideration, Hagel (2015) and Wamba et al. (2017) stated data analytics as a crucial tool of firm decision making process. This argument is further supported by researchers including Brown et al. (2011); M. Ghasemaghaei et al. (2017) and A. McAfee & Brynjolfsson (2012), who claimed that increasing popularity of big data analytics owes to its potential of making firm decisions better at quality and fast at speed. Taking all these validated facts into account, the current study hypothesizes that:

H_2: Organization's competency of big data analytics has a positive and significant impact on decision making performance of a firm.

2.3.2 Mediating role of Decision Making Performance

Referring to business management, organizational decisions have remained dependent upon the Highest Paid Person's Opinion (HiPPo) since forever (A. McAfee & Brynjolfsson, 2012). For decennium, this approach of decision making based on intuition of top executive was the only choice available (Ertemel, 2015). However by now, organizations are much interested in advanced and effective ways of enhancing their decision making performance. Subjective to this, application of big data analytics have been embedded in most of the organizational culture (Janssen et al., 2017) which poses a strong positive impact on the quality and efficiency of decisions (Ghasemaghaei et al., 2018). A study by O'Toole (2013) found that businesses are now more concerned with creating proficient teams of data scientists to go over their data and determine a direction of their decisions rather than merely taking senior executives opinion into consideration. Shah et al. (2012) in his study also emphasized on decision-making through data analytics and concluded that investment in big data can be unfavorable and return no organizational benefit unless the insights created from data are not incorporated into complex decision making as data analysis provides businesses with more and more information relevant to its external and internal environment, threat and opportunities etc. to make decisions accordingly.

It is asserted that where successful decisions are driven by using more information and taking more alternatives in account on one hand, on other hand the efficient and accurate decisions produce better firm performance (Eisenhardt & Schoonhoven, 1990). Additionally, Bolland & Lopes, (2018) claimed that future performance of businesses depends upon their decision making performance and that the better decisions assist organizations to flourish while bad decisions lead them to losses in financial or market terms. Since big data revolution, organizations in every industry now hold huge piles of external and internal data and their key interest lies in exploiting this data to gain competitive advantage through effectual decision making and enhance their firm performance (Ertemel, 2015). Past decades have witnessed the significant growth in firm performance pertinent to increased innovation and productivity, effective utilization of assets and market value, higher return on asset and equity etc. (Ertemel, 2015) based on improved decision making performance driven through big data analytics (Brynjolfsson et al., 2011). This view is also supported by Thirathon et al. (2017) in his study which illustrates that it's not only the big data which causes improved firm performance but a firm capability of driving useful insights through big data analysis which enhances the decision-making performance and thus generates better firm performance. The current study thus, proposed a hypothesis considering the fact that higher big data analytics competency improves firm performance provided that improved decision making performance is here and stated that:

H_3: Decision Making Performance acts as a mediator in positive relationship between big data analytics competency and firm performance.

2.4 Innovation Capability

One of the most critical elements in effort to attain competitive advantage in the present highly chaotic market conditions is organizations' capability to innovate (Rajapathirana & Hui, 2018). Lawson and Samson (2001) defines innovation capability as a competency of an organization to persistently blend the knowledge and new ideas to introduce novel products and processes, systems and strategies (Gloet & Samson, 2016); such that it can make a potent response to present and anticipated market and environmental challenges. Innovation capability of a firm cannot be detached from other organizational procedures and practices rather it is composed through effective integration of different type of assets, resources and capabilities (Sen & Egelhoff, 2000) which aids it to bring success in swiftly changing business environment (Rajapathirana & Hui, 2018).

2.4.1 Relationship between Innovation Capability and Firm Performance

There exists no notion of innovation, if an organization is deprived of capacity to innovate (Laforet, 2011). Existed literature in the domain of firm performance refers innovation as a bone of firm's sustainability (Rajapathirana & Hui, 2018) and asserts that innovation capability poses strong impact on an organization performance (Naala et al., 2017). Innovation capability is among the capabilities of firm which is not merely about adoption of new ideas but also the willingness to forgo such practices which are not beneficial to firms anymore (Yuan et al., 2015). Adding more to it, Breznik & Lahovnik (2016) mentioned innovation capability as the most significant out of all the capabilities any firm can have in regards to cope with changing environment and enhance firm performance. It has been stressed in studies that firms with higher level of innovation capabilities have higher productivity and economic growth comparative to those with no or minimal abilities to innovate (Saunila et al., 2014). Taking the significance of capabilities into consideration, Azubuike (2013) mentioned innovation capability of an organization as a key determinant of attaining and sustaining competitive advantage and its performance. In addition, a number of research studies argued that innovation capability of an organization assist it in surpassing its competitors, generating higher profits and increasing survival probabilities subjective to gain of competitive advantage through innovation (Agbim, 2014; Alrubaiee et al., 2015). Provided that, Su et al. (2013) recognized innovation capability as an aided tool which differentiates a firm from its competitor. It is identified that through development of innovation capabilities, business develop and applies such knowledge and skills which leads towards innovation and increased firm performance (Cabral et al., 2015). It is thus evident from previous literature that innovation capability plays a significant part in escalation of firm performance which drives the next hypothesis of current study and proposed that:

***H_4*: Organization's innovation capability has a positive and significant impact on firm performance.**

2.4.2 Mediating role of Innovation Capability

It has been majorly observed that organizations are taking new initiatives and bringing successful innovations based on useful and hidden insights provided through adoption of big data analytics. Beside, BDA have reduced time-to-market for new organizational products and services (Bean, 2018). Given that, a report by OECD has recognized big data analytics as a driver of organizational innovation and growth (OECD, 2015). Innovation, since decades, has been widely acknowledged as a bone of competitiveness and success among businesses (Chatzoglou & Chatzoudes, 2018). Organizations are needed to focus on introducing innovativeness not only in their products but processes, marketing and strategies to escalate firm performance (Tuan et al., 2016). Considering the highly competitive market and need of the hour, businesses are rushing towards adoption of big data analytics which generates high firm performance through innovation practices (Al-Jaafreh & Fayoumi, 2017). However, concept of innovation is vague without firm innovation capability (Laforet, 2011). Studies have identified that it is due to inimitable resources and capabilities of businesses which make them achieve competitive advantage and outperform their peers (Bhatt & Grover, 2005). Referring to firm innovation capability, it makes organizations capable of exploring new opportunities and introducing new products and services accordingly to satisfy customer needs, gain competitive advantage and elevate firm performance (Bowen et al., 2010; Saunila et al., 2014; Yuan et al., 2015). Based on the premise identified earlier that big data analytics drives improved firm performance through innovation and innovation without innovation capability is meaningless, while innovation capability is also a driver of high firm performance, the current study hypothesize that:

H_5: Innovation capability acts as a mediator in positive relationship between big data analytics competency and firm performance.

2.5 Research Model

Based on proposed hypothesis, current study has designed the conceptual research model with ***big data analytics competency*** as an independent while ***firm performance*** as a dependent variable with ***decision making performance*** and ***innovation capability*** as mediators.

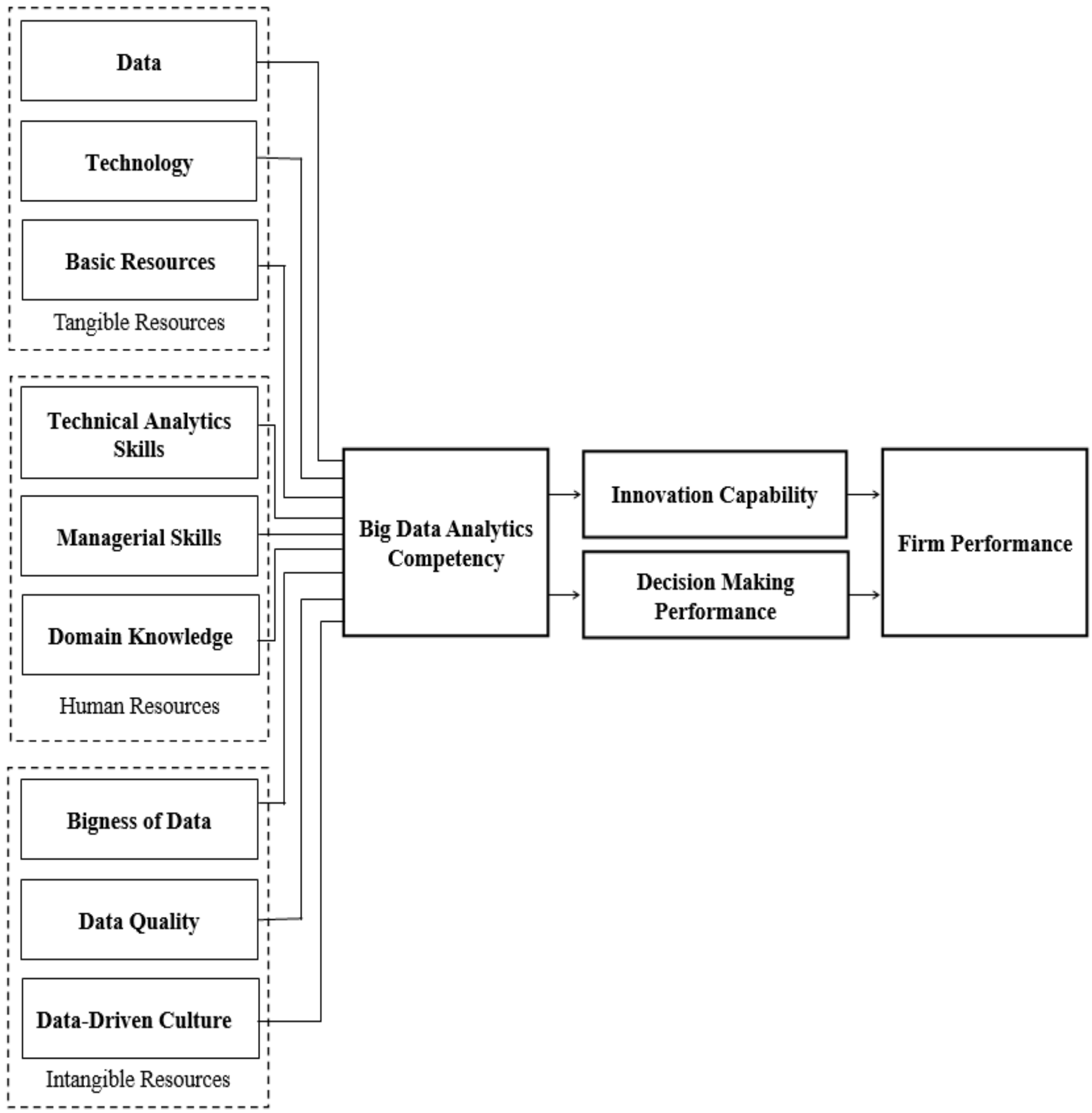

FIGURE 2.1: Research Model

2.6 Summary of Proposed Hypothesis

Current study proposed the following under-mentioned hypothesis based upon the previous literature and research gaps identified:

H_1: Organization's competency of big data analytics has a positive and significant impact on firm performance.

H_2: Organization's competency of big data analytics has a positive and significant impact on decision making performance of a firm.

H_3: Decision making performance acts as a mediator in positive relationship between big data analytics competency and firm performance.

H_4: Organization's innovation capability has a positive and significant impact on firm performance.

H_5: Innovation capability acts as a mediator in positive relationship between big data analytics competency and firm performance.

Chapter 3

Research Methodology

3.1 Research Design

Research design of current study provides the detailed view of research framework which has been adopted to ensure the effectual investigation of defined research problem and gaps. It encompasses the selection of research choices to collect and analyze the data in context of various under mentioned layers.

3.1.1 Nature of Study

A research study can be categorized either as a quantitative study or a qualitative study depending upon its nature of data collection, analysis and results (Ograjenšek & Thyregod, 2004). The current research therefore, is classified as a **quantitative study** as it has analyzed the questionnaires based collected data statistically and is objective in nature.

3.1.2 Research Philosophy

A research study can fall under any of the four types of research philosophies namingly pragmatism, positivism, realism and interpretivism subjected to assumptions, nature and development of knowledge (Saunders et al., 2008). The current research has adopted the **positivism** research philosophy as the hypothesis are developed based on the existing theory, research is conducted in a value-free way and the results produced by the quantitative analysis of well-organized and structured data are strictly objective and reliable.

3.1.3 Research Approach

Two of the research approaches are defined as deductive approach and inductive approach owing to various characteristics of research to be carried out (Soiferman, 2010). The current research has followed the **deductive** research approach as hypothesis are developed based upon a theory and data is then collected in a highly structured form to verify the defined casual relationships between variables by quantitative analysis.

3.1.4 Research Strategy

Saunders (2008) mentioned seven different research strategies in his research 'onion' for the collection of data to undertake a research depending upon the resources, a researcher has. These strategies included survey, experiment, case study, grounded theory, ethnography, action research and archival research. The current study however went with the **survey-questionnaire** strategy for data collection as it allows to collect standardized data from a generous size of population in an efficient and economical way (A Adams, 2008).

3.1.5 Research Choice

Depending upon the choices of data collection and analysis technique, three different research choices are provided by Saunders (2008) as mono-method, multi-method and mixed methods. Out of three, the present study opted for the **mono-method** as it has used only quantitative data collection technique (i.e. questionnaire), with quantitative data analysis procedures (Saunders et al., 2008).

3.1.6 Unit of Analysis

Unit of analysis refers to the main entity or object which is to be analyzed in a research study and it is categorized into four different levels as: (i) individual level (such as employees, supervisors, top management, customers etc.), (ii) group level (such as departments, teams, families, divisions, project teams etc.), (iii) organizational level (such as business corporation, educational institutions, not-for-profit organizations, unions etc.) and (iv) social artifacts level (such as social interaction etc.) (Dolma, 2010). In the present study, the unit of analysis is of **organization level** as corporate units of telecommunication and banking sector in Pakistan were analyzed in this research; their big data analytics competency, their decision-making performance, their innovation capability, and their market and operational performance.

3.1.7 Time Horizon

Subjected to the time span of data collection, a research study can be classified either as a longitudinal study or a cross-sectional study (Saunders et al., 2008). The current research study is **cross-sectional study** as the data has been collected at one time within one month.

3.2 Population and Sample

3.2.1 Population

Population in context of research is referred to as the entirety of the subjects or objects which complies with the defined research specifications (Polit & Hungler, 2006). In the present study, the relevant population circle has covered the data managers, data specialists, data scientists, data engineers, operation managers, business analysts and executives of such firms which are practicing big data analytics in their units; specifically of telecommunication and banking corporations across the Pakistan.

It has been estimated that main number of banks in Pakistan is around 45 which includes Microfinance banks too (SBP, 2016) while being specific towards cellular public land mobile and landline PSTN in telecommunication sector, 4 major mobile operators and 2 main landline operators exists in Pakistan (PTA, 2017), however these organizations have extended their branch network across the country which increases the overall population of defined sectors. A report by Pakistan Telecom Authority shows an estimated number of employees in telecom sector as 212,731 (PTA) whereas 162,009 employees in banks of Pakistan (KPMG, 2018). Subjective to observations, current study makes a realistic assumption that telecom sector has around 15% of employees working in analytics and management area whereas banking, being a financial industry has around their 5% of employees engaged in domain of analytics and management. Based on these assumptions, the sample size has been driven to conduct the study.

3.2.2 Sample

Sample refers to a selected set of objects or subjects from a population to be investigated to make the analysis convenient (on finite number of units) such that the generated results can be generalized back to the population being represented by the selected sample (Webster, 1983). For the current study, sample size has been determined using Cochran's Sample Size formula (Machin et al., 2008) which is:

$$n_o = \frac{Z^2pq}{e^2} \tag{3.1}$$

Here n_o = Sample Size, Z = z value at confidence interval 95 which is 1.94, p = estimated population proportion, q = 1-p and e = desired level of precision.

Putting the required values first for telecom sector, where p = 0.15, q = 0.85 and e = 0.05 generates sample size no = 191.94, whereas for banking industry p = 0.05, q = 0.95 and e = 0.05 produced sample size of no = 75.10.

Therefore in current study, the sample size evaluated was 267 units and the sampling technique used was **convenience** sampling, a non-probabilistic sampling technique whereas data had been collected through an online questionnaire survey.

Referring to Pakistan telecom and banking industry, Table 3.1 represents the firms chosen as a sample to collect responses.

TABLE 3.1: Sample

Pakistan Telecommunication Industry	**Pakistan Banking Industry**
Jazz (Mobilink & Warid Telecomm)	Habib Bank Limited
Telenor	United Bank Limited
Zong	National Bank of Pakistan
Ufone	Allied Bank Limited
PTCL	JS Bank
	Bank Alfalah
	Meezan Bank
	Bank of Punjab
	Khushhali Microfinance Bank

3.2.3 Procedure

A digital survey questionnaire (Google form) was composited by demographics and constructs of big data analytics competency, decision making performance, innovation capability and firm performance and disseminated among 400 management and data related employees of different telecom companies and banks via their professional profiles on LinkedIn platform. Such telecommunication companies and banks were first foraged which are using big data analytics in their system so to approach their employees to get questionnaires filled. Out of 400 questionnaires distributed, 326 responses were received which makes 81.5 percent. 300 useable and complete responses were then separated out to get considered, in which 74% of telecom and 26% were of banking sector and was close enough to determined sample size. Data collected was self-administered and the factors based upon which some of the responses were deemed vague included: (a) Incomplete/Partially filled surveys i.e. questions were left unanswered; (b) Blindly filled surveys i.e. respondent selected contrary response to a questions with obvious answers e.g. the response to a question, 'In our organization, we process high volume of data.' can vary from agree to strongly agree but it can never be disagree as one of the vital characteristics of big data is high volume; (c) Biased responses i.e. the respondent went with the same response throughout the survey e.g.; all questions were answered as "Strongly Agree".

3.2.4 Ethical Consideration

The current research ensures that the confidentiality of participants is of prime concern. Survey questionnaire was accompanied with an introductory letter to provide respondent with justification of data collection, assurance of using it purely for academic purpose and a promise of not blabbing the information out ever.

3.3 Instrumentation

In the present study a digital questionnaire was used as an instrument for data collection. The variables and the scales however have been adopted from the previous research studies and was composited in such a way where respondent rated each item in accordance to the involvement of big data analytics, decision-making performance, innovation capability and firm performance. All the items included were rated on 7-point Likert scales ranging from 1 to 7 i.e. from strongly disagree to strongly agree. Besides, demographic information such as organization name, sector, designation, age, years of experience, total experience in current organization and total number of employees have been recorded as a part of data collection.

3.3.1 Big Data Analytics Competency

Instrument adopted to measure Big Data Analytics Competency of a firm was derived by the integration of firm resources such as data, technology, basic resources, technical analytics skills, managerial skills, data-driven culture (Gupta & George, 2016), bigness of data, domain knowledge (Maryam Ghasemaghaei et al., 2018) and data quality (R. Y. Wang & Strong, 1996). Total of 28 items were included which had been subdivided among already mentioned resource dimensions. The scale for data included 3 items and one of the sample items is “1= We have access to very large, unstructured, or fast-moving data for analysis.”, bigness of data included 2 items and one of the sample items is “1= In our organization, we process high volume of data.”, data quality included 3 items and one of the sample items is “1= In our organization, data used in data analytics is reliable.”, technology included 4 items and one of the sample items is “1= We have explored or adopted different data visualization tools.”, basic resources included 2 items and one of the sample items is “1= Our big data analytics projects are given enough time to achieve their objectives.” , technical skill included 3 items and one of the sample items is “1= We provide big data analytics training to our own employees.”, managerial skills included 5 items and one of the sample items is “1= Our big data analytics managers have a good sense of where to apply big data.”, domain knowledge included 4 items and one of the sample items is “1= In our organization, there is a high level of knowledge of the organizational goals and objectives.” and data-driven culture included 2 items and one of the sample items is “1= We are willing to override our own intuition when data contradict our viewpoints.” The reliability value of all the constructs was more than 0.7 in previous studies (Maryam Ghasemaghaei et al., 2018; Gupta & George, 2016).

3.3.2 Decision Making Performance

Decision-Making Performance of a firm was measured by the instrument developed by Jarupathirun & Zahedi, (2007) which is integration of decision quality and decision efficiency. Total of 4 items were included and one of the sample items is

"In our organization, decision outcomes are often reliable." The reliability value of scale was greater than 0.9 in prior studies (Maryam Ghasemaghaei et al., 2018; Gupta & George, 2016).

3.3.3 Innovation Capability

Instrument developed by Yilmaz & G., (2008) was used to measure Innovation Capability of a firm. Total of 6 items were included and one of the sample items is "Our firm has an organizational culture and a management comprehension that support and encourage innovation.", The reliability value of scale was 0.86 in previous study (Yilmaz & G., 2008).

3.3.4 Firm Performance

Firm Performance was measured by the instrument developed by Ravichandran & Lertwongsatien, (2005) and N. Wang et al., (2012) which is composition of market performance and operational performance. Total of 7 items were included which had been subdivided among already mentioned dimensions. The scale for market performance included 4 items and one of the sample items is "1= We have entered new markets more quickly than our competitors." And the scale for operational performance included 3 items and one of the sample items is "1= Our productivity has exceeded that of our competitors." The reliabilities values for the scales were greater than 0.8 in the prior studies (Ravichandran et al., 2005; N. Wang et al., 2012).

3.4 Sampling Frequency

Frequency shows the percent proportion of survey data set. In current study, the demographic frequency provides the percent proportion of sector, age, years of experience, total experience in current organization and total number of employees in current organization of sample data.

Table 3.2: Sampling Frequency

Items	Sector	Age	Total Exp	Exp in Current Organization	Total Employees	Frequency	Cumulative %
Telecom	74%					22	74%
Banking	26%					78	100%
20–25yr		7.70%				23	7.70%
26–30yr		50.70%				152	58.40%
31–35yr		35.00%				105	93.30%
36 above		6.70%				20	100%
0–5yr			32.30%	89.00%		97	32.30%
6–10yr			54.30%	8.30%		163	86.60%
11–15yr			12.00%	2.70%		36	98.60%
16above			1.30%	0.00%		4	100%
Below 50					0.00%	0	0.00%
51–100					0.00%	0	0.00%
101–150					0.00%	0	0.00%
150above					100%	300	100%
Sample Size						300	

The aforementioned Table 3.2 illustrates that in sample data collected to represent the population, 74% of the sample was from telecommunication sector and 26% from banking and finance and as far as age is of concern, 50.7% of sample fall between 26 – 30 yrs, 35% between 31 – 35 yrs, 7.7% between 20 – 25 yrs and 6.7% is above 36yrs. Next, the total experience of employee has also been investigated and it has been found that 54.3% of sample was having experience of 6 – 10 yrs, 32.3% was with experience of 0 – 5 yrs, 12% with 11- 15 yrs and 1.3% with more than 16 and above years of experience. While the experience of employees in the current organization was also asked to assure that they have spent quite enough of a time to answer the questions relevant to their firm. The evaluated ratio shows that 89% of sample was having experience of 0 – 5 yrs in the current organization, 8.3% was with experience of 6 – 10 yrs and 2.7% with 11- 15 yrs. Furthermore, number of employees in sample organization has also been determined to have an idea about either the body operates at large or small scale and results show that all the employees were part of the big organizations with number of employees more than 150.

In addition, the pie chart representation of respondent's demographic distribution has been shown below:

3.4.1 Sector

74% of responses were collected from telecom sector while 26% from banking sector.

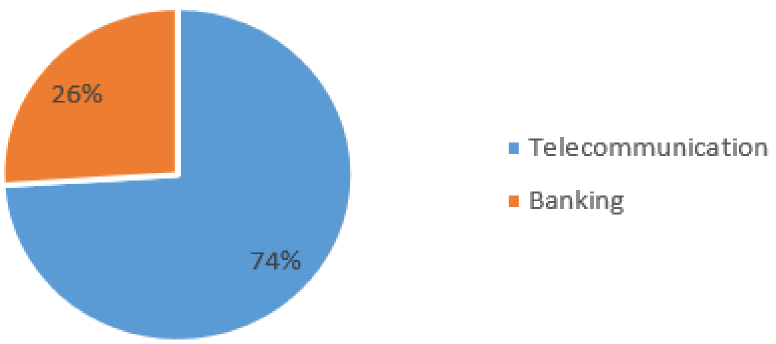

Figure 3.1: Pie Chart Representation of Sector Distribution

3.4.2 Age

7.70% (rounded off as 8%) of responses were collected from age group of 20 - 25 years, 50.70% from age group of 26 - 30 years, 35% from age group of 31 - 35 years and 6.70%(rounded off as 7%) of the respondents were of age more than 36 years.

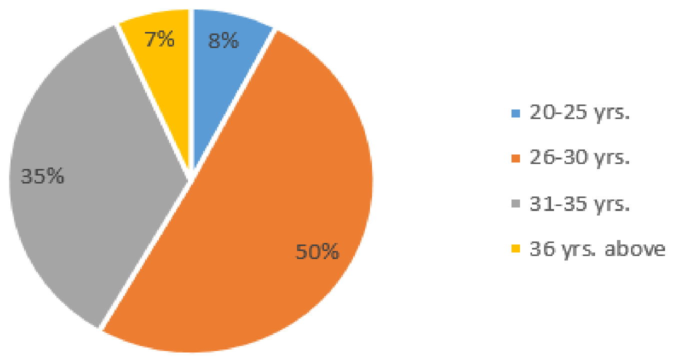

FIGURE 3.2: Pie Chart Representation of Age Distribution

3.4.3 Total Experience

32.30% of responses were collected from group of employees having 0 - 5 years of total experience, 54.30% (rounded off as 55%) were having 6 - 10 years of total expereince, 12% were having 11 - 15 years of total experience and 1.30% of the respondents were having more than 16 years of total experience.

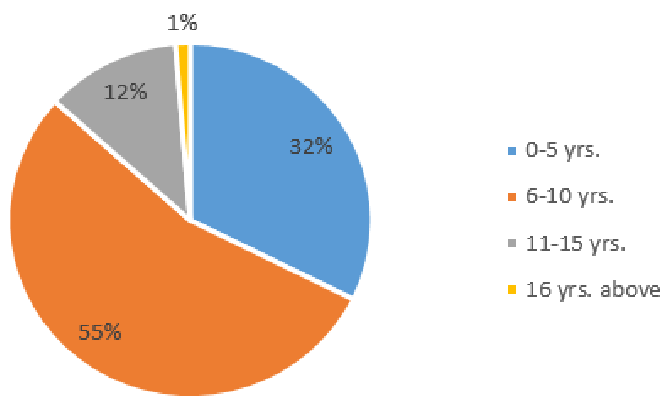

FIGURE 3.3: Pie Chart Representation of Total Experience

3.4.4 Experience in Current Organization

89% of responses were collected from group of employees having 0 - 5 years of experience in current organization, 8.30% were having 6 - 10 years f expereince, 2.70% (rounded off as 3%) were having 11 - 15 years of experience and 0% of the respondents were having more than 16 years of experience in current organization.

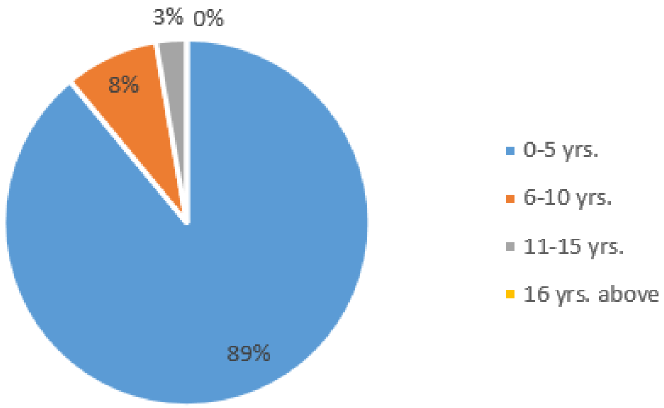

Figure 3.4: Pie Chart Representation of Experience in Current Organization

3.5 Instrument Pilot Study

Authentication and reliability of scales has always remained the primary concern of research studies. Although the instrument used in the current study is adopted from previous research studies and its reliability is already tested yet due to factors like culture difference, organization size etc., before proceeding towards larger scale, a proactive approach was considered to conduct a pilot test for it to avoid risks related to wastage of resources such as time. Cronbach's alpha reliability is used in the current study to test the relevancy, reliability and consistency of the items. A pilot study was performed on 50 survey responses to evaluate the internal consistency of each instrument used. These surveys were filled by IT and management related employees of firms within the sphere of telecom and banking sector of Pakistan. In the next Table 3.3, results of pilot study have been recorded including their sources, total number of items and Cronbach's alpha.

TABLE 3.3: Reliability Statistics for Pilot Study

Variable	Cronbach's Alpha	Items
Big Data Analytics Competency	0.923	28
Decision-Making Performance	0.772	4
Innovation Capability	0.714	6
Firm Performance	0.868	7

The computed results clearly show that scale of each instrument has high alpha within range of 0.7 to 1.0 which is sufficient enough to reach the acceptable reliability ($\alpha > 0.7$) and validates that the items of each variable are worthy to be analyzed so to reach at required results.

3.6 Factor Analysis

Factor analysis is a statistical method to enhance the result by trimming items which are in inter-construct relationship. Besides, it deals with issue of construct validity. It identifies the pattern in which items form relationship while those which are cross loaded were eliminated and pattern matrix is generated, which is reported below in Table 3.4.

Table 3.4: Pattern Matrix

	Component												
	1	2	3	4	5	6	7	8	9	10	11	12	13
BDAC5	0.82												
BDAC4	0.791												
DMP3		0.841											
DMP1		0.8											
DMP2		0.786											
DMP4		0.678											
BDAC3			0.832										
BDAC1			0.609										
BDAC2			0.55										
BDAC22				0.893									
BDAC18				0.744									
BDAC21				0.711									
BDAC19				0.689									
BDAC20				0.508									
BDAC10					0.82								
BDAC9					0.819								
BDAC11					0.802								
BDAC12					0.725								
FP5						0.836							
FP6						0.827							
FP7						0.816							
BDAC16							0.803						
BDAC17							0.8						
BDAC15							0.362						
FP4								0.846					
FP3								0.834					
FP1								0.774					
FP2								0.708					
IC2									0.671				
IC1									0.577				
IC3									0.756				
IC5									0.646				
IC4									0.721				
IC6									0.517				
BDAC13										0.633			
BDAC14										0.461			
BDAC24											0.785		
BDAC23											0.726		
BDAC26											0.691		
BDAC25											0.581		
BDAC27												0.587	
BDAC28												0.542	
BDAC8													0.783
BDAC6													0.745
BDAC7													0.704

3.7 Data Analysis Tool and Technique

The present study used **SPSS 20** to analyze the collected data by carrying out number of under-mentioned tests:

- Reliability analysis
- Normality analysis
- Frequency distribution
- Descriptive statistics
- Correlation analysis
- Regression analysis
- Mediation analysis

Chapter 4

Data Analysis and Results

This chapter is composed of analysis of data gathered to investigate the defined relationships between different variables. Descriptive statistics, normality analysis, reliability analysis, correlation analysis, regression analysis and mediation analysis has been done and narrated to build the foundation for approval or rejection of proposed hypothesis.

4.1 Normality Analysis

Prior to perform statistical analysis of data, it is always assumed that the data which has to be analyzed follows the normal distribution i.e. Gaussian distribution (Rani Das et al., 2016). There exists a likelihood of inaccurate and unreliable results if the data are not normally distributed (Ghasemi & Zahediasl, 2012). The current study used two tests to check the normality of collected data.

1. Skewness to check the symmetry of data distribution
2. Kurtosis to check the height/sharpness of data distribution

The two tests used histograms to visually inspect the skewness and kurtosis of each construct. In addition, box-plot and Q-Q plot were used to identify the outliers. The cutoff value adopted for acceptable skewness and kurtosis coefficient of data was between -1.96 to +1.96 (Gaskin, 2011). Results of both the tests are reported in Table attached in Appendix C, which shows that data is normally distributed.

4.2 Reliability Analysis

Reliability analysis as the name shows examine the reliability of scale to which the results generated are consistent and Cronbach's alpha test is used to examine the internal consistency of scale most frequently when Likert scale is adopted. Given that, it provides the assurance either or not used Likert scale is reliable. The accepted value of reliability is greater than 0.7 ($\alpha > 0.7$) to consider the scale reliable enough to be used.

The current study used 7-point Likert scale for all the items which are analyzed and the findings for reliability analysis calculated using SPSS 20 are below in the Table 4.1;

Table 4.1: Cronbach's Alpha Reliabilities

S.no	**Variable**	**Cronbach's Alpha**	**Items**
1	Big Data Analytics Competency	0.929	28
2	Decision-Making Performance	0.771	4
3	Innovation Capability	0.718	6
4	Firm Performance	0.844	7

In reference to the above Table 4.1, the computed value of alpha reliability for big data analytics competency is 0.929, for decision making performance it is 0.771, for innovation capability it is 0.718 and for firm performance it is 0.844. Analyzing it collectively, value of ($\alpha > 0.7$) for each variable thus illustrated that scale of each variable is reliable to be adopted in the contextual setting of Pakistan.

4.3 Descriptive Statistics

Descriptive statistics of data assists in understanding the basic characteristics of sample data by providing the statistical summaries regarding the sample and the measures which drive the description of what the data really indicates. Along with, descriptive analysis of data makes it possible to evaluate the normality of data distribution (Kale, 2013).

The data in the present study was analyzed descriptively with respect to measure of central tendency and variability where measure of central tendency provides a single central value of the entire data distribution which can most accurately represent the data while variability provides a value which shows how spread are the data from central value (Manikandan, 2011); however, both the measures vary from variable to variable. The measure of central tendency has been computed in terms of three most widely known types i.e. Mean, Median and Mode while variability is measured in terms of Standard deviation. In addition Maximum and Minimum value has been determined to evaluate the largest and smallest value of data distribution across each variable. Furthermore, the software tool used to evaluate the descriptive analysis of data set in tabular form was SPSS 20 and the data set is analyzed on 7-point Likert scale where 1 represents 'Strongly disagree' and 7 represents 'Strongly agree'.

Table 4.2: Descriptive Statistics

Variable	**N**	**Mean**	**Median**	**Mode**	**St.d**	**Minimum**	**Maximum**
BDAC	300	5.8325	5.8750	5.61^a	0.67012	3.32	7.00
DMP	300	5.4192	5.5000	6.50	1.12710	1.00	7.00
IC	300	5.6844	5.8333	6.17	0.85564	3.17	7.00
FP	300	5.4143	5.4286	5.71^a	0.98695	2.00	7.00

Note: *The superscript a shows that multiple modes exist. The smallest value is shown*

Table 4.2 provides the descriptive statistics of variables examined in the current research study. Total numbers of rows included in the table are 5 and columns are 8 where each column represents the statistical data under different measures however, the first header column represents the **variables** where i) Big data analytics competency is independent variable, ii) Decision-making performance is first mediator, iii) Innovation capability is second mediator and iv) Firm performance is dependent variable. The first column namingly ***N*** gives the sample size of data across each variable which is 300. The second column shows the ***Mean*** across each variable which gives the average value where most of data sample fall across each variable. The statistical value shows that mean for big data analytics competency is 5.83, for decision-making performance it is 5.41, for innovation capability it is 5.68, and for dependent variable firm performance it is 5.41. Collectively analyzing, the mean value across each variable is higher than 5 which indicates that most responses across each variable fluctuates between slightly agree to strongly agree. Next, the third column of the table gives the ***Median*** value of data across each variable which is actually the central value which parts the distribution into two equal sets where 50 percent are above the median value and 50 percent are below. The statistical value shows that median for big data analytics competency is 5.87, for decision-making performance it is 5.50, for innovation capability it is 5.83 and for firm performance it is 5.42. The median value across each variable is above than 5. The fourth column represents the ***Mode*** with respect to each variable which gives the most repeated value in the distribution. The statistical data in the aforementioned table shows that mode value for big data analytics competency is 5.61, for decision-making performance it is 6.50, for innovation capability it is 6.17 and for firm performance it is 5.71 that means mostly responses fall in 'Agree' category. The fifth column provides the value for ***Standard deviation*** which represents the dispersion of data set in relation to mean value. The observed value shows of standard deviation for big data analytics competency is 0.67, for decision-making performance it is 1.12, for innovation capability it is 0.85 and for firm performance it is .98. Sixth and Seventh column of the table labeled as ***Minimum*** and ***Maximum*** demonstrates the extrema of the distribution. The minimum value shows for big data analytics competency is 3.32, for decision-making performance it is 1.00, for innovation capability it is 3.17 and for firm performance it is 2.00 while the maximum value for all the four variables is 7.00. These observed statistical values across all the variables represent the average and frequencies of the distribution.

4.4 Correlation Analysis

The distinguishing feature of correlation analysis is to determine the association or relation between variables and produce correlation coefficient as a result. In compliance to the Pearson correlation analysis, the value of correlation coefficient can range from -1 to +1 determining the strength of association; the mathematical symbols + and – here however indicates the mannerism of relation either as negative or positive. If correlation is positive, it means that variation in one variable cause the other variable to increase or decrease in the same direction while oppositely if the association between variables is negative, the variation in one variable will cause the other variable to vary in contrary direction. Additionally, if the value of correlation coefficient is zero, this gives the indication of denial for existence of any sort of linear relationship between two variables (Gogtay & Thatte, 2017).

The correlation analysis in the current study helps in determining the association between big data analytics competency, firm performance, decision-making performance and innovation capability. The correlation analysis of the variables is done using SPSS 20 and the findings are mentioned below in the Table 4.3;

Table 4.3: Correlation Coefficients

S.no	**Variables**	**1**	**2**	**3**	**4**
1	Big Data Analytics Competency	1			
2	Decision Making Performance	0.540^{**}	1		
3	Innovation Capability	0.677^{**}	0.606^{**}	1	
4	Firm Performance	0.636^{**}	0.530^{**}	0.550^{**}	1

Note: *** shows that correlation is significant at 0.01 level.*

The preceding Table 4.3 shows the values for correlation co-efficient for relation between different variables. The determined value for correlation efficient ($\boldsymbol{r}$) between big data analytics competency and firm performance is r = 0.63 which explains that a positive relation exist between both the variable such that increase or decrease in one variable will make the other variable to move in same direction.

Next, the value of correlation coefficient found between big data analytics competency and decision making performance is r = 0.54 which indicates that there is a positive bond between the two variables. Moreover, the correlation coefficient between decision making performance and firm performance is r = 0.53 which also shows the positive association between the two variables.

Lastly, the correlation coefficient between innovation capability and big data analytics competency came out to be r = 0.67 which shows the presence of positive connection between two considered variables. The correlation coefficient between innovation capability and firm performance is r = 0.55 which affirms the existence of positive association within both variables. The correlation analysis thus delineated the existence of bond and positive or negative behavior between variables.

4.5 Regression Analysis

Regression Analysis is one of the most frequently used method to analyze data. It is considered as an enhanced form of correlation analysis and it depicts the dependency of a variable on one or more predictors. Given that, regression analysis assists the investigator to predict a measure of dependent variable based on independent variable (Vito et al., 2015).

It is assumed that linear regression analysis can only be performed for quantitative variables having linear relationship between them and data being normally distributed with no outliers in it (Stephanie, 2018). Subjective to fulfillment of all assumptions, current study thus analyze the data through regression analysis.

The present research study used SPSS 20 to perform regression analysis between dependent variable organization performance and predictor big data analytics competency. Findings of the regression analysis are under-mentioned.

TABLE 4.4: Model Summary

Model	***R***	R^2	$\triangle R^2$
1	0.636	0.404	0.402

The aforementioned Table 4.4 demonstrated the following results:

1. Correlation coefficient $(R) = 0.636$ which shows that significant relation exist between both the variables which support $\mathbf{H_1}$**:** Organization's competency of big data analytics has a positive and significant impact on firm performance.
2. Coefficient of determination $(R^2) = 0.404$ which explains that rate of change in dependent variable i.e. firm performance that can be explained by independent variable i.e. big data analytics competency is 40.4%.
3. Adjusted R $(\triangle R^2) = 0.402$ which explains that effect of R^2 will be reduced to 40.2% if it is biases-free.

Beside these results, regression analysis provides the table of ***coefficients*** to predict value of dependent variable through predictor.

TABLE 4.5: Coefficients

	Unstandardized		**Standardized**	**t**	**Sig.**
	B	**Std. Error**	**Beta**		
(Constant)	- 0.46	0.388		- 0.12	0.905
BDAC	0.936	0.066	0.639	14.216	0.000

Note: *Dependent Variable: FP*

Table 4.5 helps in examining either or not the independent variable significantly contributes to the model by analyzing the value of last column which is Sig. The cutoff point for this value is 0.005 and the computed value 0.000 shows that firm big data analytics competency statistically and significantly contributes to the model in which BDAC is independent variable and FP is dependent variable. Furthermore, the values in the column B assist in building the linear regression equation for the model so to predict/evaluate the value of dependent variable through independent variable. The general form of linear equation is:

$$Y = a + b(X) \tag{4.1}$$

The linear regression equation created for the present model using the extracted information is:

$$FP = -0.46 + 0.936(BDAC) \tag{4.2}$$

where FP = Firm Performance (dependent variable), a = - 0.46, b = 0.936, $BDAC$ = Big data analytics competency (predictor).

4.6 Mediation Analysis

Mediation analysis helps to determine the effect of third variable on outcome of relation between two variables such that it assist in examining either the mediator variable is in causal sequence between dependent and independent variable or not (MacKinnon et al., 2007). The current research study used two mediators in relation between BDAC and FP.

4.6.1 Mediation with Bootstrapping

Mediation Analysis is first done by using bootstrapping. Bootstrap allows "approximating the sampling distribution of a statistics". It uses bootstrap samples generated through random re-sampling with replacement from the sample data (Singh & Xie, 2008).

4.6.1.1 Decision Making Performance as a Mediator

Mediation analysis for decision-making performance between BDAC and FP has been performed using Hayes & Preacher, (2008) SPSS macro for multiple mediation indirect tool while the size of bootstrap sample was 5000 and level of confidence interval (CI) was 95%. Findings of the test are recorded below in the Table 4.6;

TABLE 4.6: Effects Using DMP as a Mediator

Paths	**B**	**t**	**p**
BDAC → DMP (a path)	0.9088	11.0839	0.0000
DMP → FP (b path)	0.2351	5.2750	0.0000
BDAC → FP (c path)	0.9362	14.2161	0.0000
BDAC → FP (c'path)	0.7266	9.6393	0.0000

Note: *DV: FP, IV: BDAC, MED: DMP*

The preceding Table 4.6 illustrates that a significant positive relation exists between BDAC and DMP (B = 0.90, t(297) = 11.0839, p = 0.0000) which provides evidence for acceptance of $\mathbf{H_2}$. Next, the results show that DMP has significant positive association with FP (B = 0.23, t(297) = 5.2750, p = 0.0000). Furthermore, it can be observed from the computed results there is a presence of significant positive bond between BDAC and FP in case of direct effect (B = 0.72, t(297) = 9.6393, p = 0.0000) which supports $\mathbf{H_1}$ and total effect (B = 0.93, t(297) = 14.2161, p = 0.0000) which is different from direct effect. Here, if the difference between direct and total effect is analyzed (0.2096 of change in effect), it shows that decision making performance is partially mediating the relationship between BDAC and firm performance. However, as the mediating effect is present, thus this stands the hypothesis $\mathbf{H_3}$.

The bootstrapping results for indirect effects can be demonstrated from the undermentioned Table 4.7.

TABLE 4.7: Bootstrapping Results for Indirect Effect through DMP

	Data	**LLCI 95%**	**ULCI 95%**
TOTAL	0.2137	0.1098	0.3227
DMP	0.2137	0.1098	0.3227

Note: *LL: Lower Limit, UL: Upper Limit,*
CI: Confidence Interval, Bootstrap sample size: 5000

Results in Table 4.7 indicates that decision making performance partially mediates the relation between BDAC and FP as there exist no zero value between lower limit (0.1098) and upper limit (0.3227) within the bootstrapped 95% confidence interval, thus $\mathbf{H_3}$ is accepted.

Additionally, the pictorial description of results for mediation effect of decision making performance on independent variable big data analytics competency and dependent variable firm performance can be viewed through Figure 4.1 below.

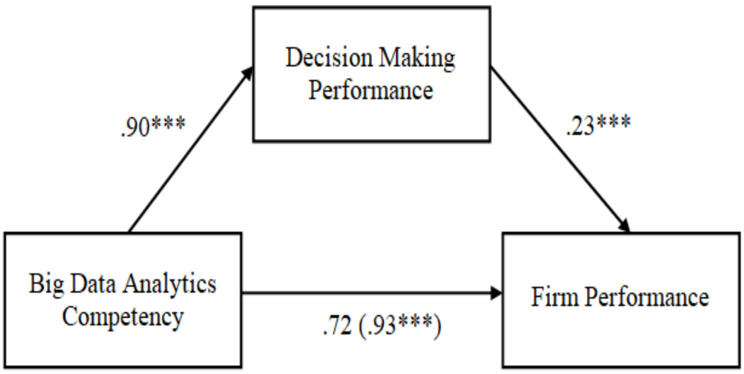

FIGURE 4.1: Effect of BDAC on FP through DMP
Note: **p< .05, **p<.01, ***p<.001*

Above Figure 4.1 indicates the values of coefficients through each path. It can be seen that all values are significant at p = 0.0000 which provides evidence for existence of mediation in the model due to decision making performance.

4.6.1.2 Innovation Capability as a Mediator

Likewise DMP, mediation analysis for innovation capability between BDAC and FP has been performed using Hayes & Preacher (2008) SPSS macro for multiple mediation indirect tool while the size of bootstrap sample was 5000 and level of confidence interval was 95%. Findings of the test are reported next in the Table 4.8.

Table 4.8: Effects Using IC as a Mediator

Paths	**B**	**t**	**p**
BDAC → IC (a path)	0.8650	15.8986	0.0000
IC → FP (b path)	0.2700	3.9434	0.0001
BDAC → FP (c path)	0.9362	14.2161	0.0000
BDAC → FP (c'path)	0.7027	8.0377	0.0000

Note: *DV: FP, IV: BDAC, MED: IC*

The aforementioned Table 4.8 demonstrates that a significant positive relation exists between BDAC and IC (B = 0.86, t(297) = 15.8986, p = 0.0000). Next, the results show that IC has significant positive association with FP (B = 0.27, t(297) = 3.9434, p = 0.0001) which provides acceptance for $\mathbf{H_4}$. Moreover, it can be analyzed from the evaluated results that the direct effect of BDAC on FP (B = 0.70, t(297) = 8.0377, p = 0.0000) and total effect (B = 0.93, t(297) = 14.2161, p = 0.0000) showed some proportion of change which provides evidence of mediating behavior due to innovation capability. Although the observed change in effect is not major (0.2335), however the presence of mediation due to innovation capability can not be denied. This shows that relationship between BDAC and FP is partially mediated by the presence of innovation capability and therefore stands the hypothesis $\mathbf{H_5}$. Furthermore, the bootstrapping results for indirect effects can be demonstrated from the under-mentioned Table 4.9.

Table 4.9: Bootstrapping Results for Indirect Effect through IC

	Data	**LLCI 95%**	**ULCI 95%**
TOTAL	0.2336	0.1091	0.3694
IC	0.2336	0.1091	0.3694

Note: *LL: Lower Limit, UL: Upper Limit,*
CI: Confidence Interval, Bootstrap sample size: 5000

Results in Table 4.9 indicates that innovation capability partially mediates the relation between BDAC and FP as there exist no zero value between lower limit (0.1141) and upper limit (0.3762) within the bootstrapped 95% confidence interval, thus $\mathbf{H_5}$ is accepted.

In addition, the pictorial description of results for mediation effect of innovation capability on independent variable big data analytics competency and dependent variable firm performance can be visualized through Figure 4.2 below.

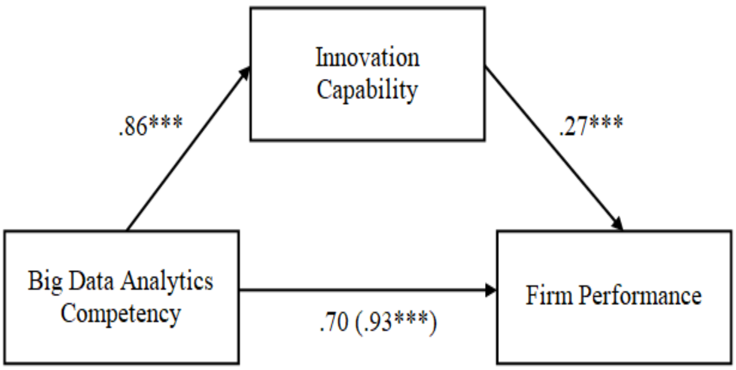

Figure 4.2: Effect of BDAC on FP through IC

Note: **p< .05, **p<.01, ***p<.001*

Above Figure 4.2 depicts the values of coefficients across each path. It can be observed that all values are significant at p = 0.0000 which stands the existence of mediation in the model due to Innovation Capability.

4.6.2 Dual Mediation with Process v2 16.3 Macro Tool

Hayes (2017) gave 74 such models which interpret different roles of mediator and moderator in relation between dependent and independent variable with their direct and indirect effects. Referring to Hayes (2017) models, Model 6 has been adopted in this present study for mediation analysis in which two mediators innovation capability and decision-making performance effects the direct relation of big data analytics competency and firm performance. Figure 4.3 below shows the generic template for Model 6.

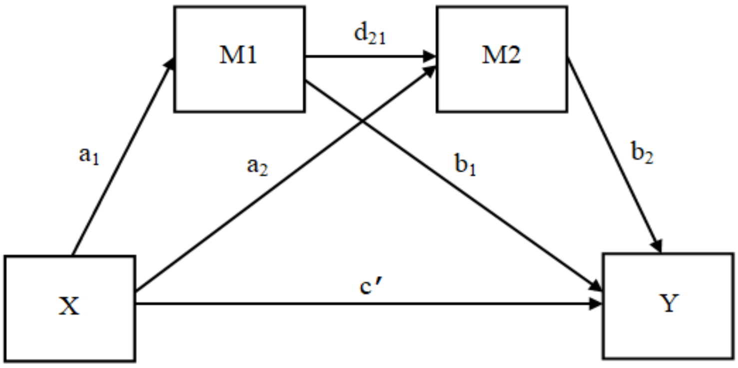

FIGURE 4.3: Model 6

Here, in this model X is an independent variable, Y is dependent variable, while M1 and M2 both are mediators. In accordance to Model 6, results generated for the current study are documented below in tables for different outcomes. Table 4.10 shows the outcome for Decision Making Performance.

TABLE 4.10: Outcome for DMP

	Effect	**p**	**LLCI 95%**	**ULCI 95%**
BDAC	0.9088	0.0000	0.7474	1.0701

Table 4.10 shows BDAC causes a significant effect on DMP (B = 0.90, t(298) = 11.089, p = 0.0000) and there exist no zero value between LL (0.7474) and UL (1.0701) within the bootstrapped 95% confidence interval. This thus built the basis for acceptance of $\mathbf{H_2}$.

Next, Table 4.11 shows the outcome for Innovation Capability.

TABLE 4.11: Outcome for IC

	Effect	**p**	**LLCI 95%**	**ULCI 95%**
DMP	0.2570	0.0000	0.1872	0.3269
BDAC	0.6314	0.0000	0.5139	0.7489

The above Table 4.11 shows that effect of DMP on IC is significant (B = 0.25, t(297) = 7.2407, p = 0.0000) and the effect of BDAC on IC is significant too (B = 0.63, t(298) = 10.5747, p = 0.0000) as interval between LL and UL doesn't include zero value.

The subsequent Table 4.12 includes the outcome for Firm Performance.

TABLE 4.12: Outcome for FP

	Effect	**p**	**LLCI 95%**	**ULCI 95%**
DMP	0.1950	0.0001	0.1004	0.2895
IC	0.1562	0.0318	0.0137	0.2987
BDAC	0.6240	0.0000	0.4519	0.7960

The aforementioned Table 4.12 illustrates that DMP effects FP significantly (B = 0.19, t(296) = 4.0574, p = 0.0001). Next, the significant effect of IC on FP (B = 0.15, t(296) = 2.1574, p = 0.0318) justifies the existence of positive relationship between both the variables which laid the foundation for approval of $\mathbf{H_4}$. Last row of the table shows that BDAC has significant effect on FP (B = 0.6240, t(297) = 7.1380, p = 0.0000) which makes the proposed hypothesis $\mathbf{H_1}$ approved. Additionally, there is no presence of zero value between LL and UL in 95% confidence interval.

Subjected to the computed results, Figure 4.4 below depicts the conceptual diagram of Model 6 for current study.

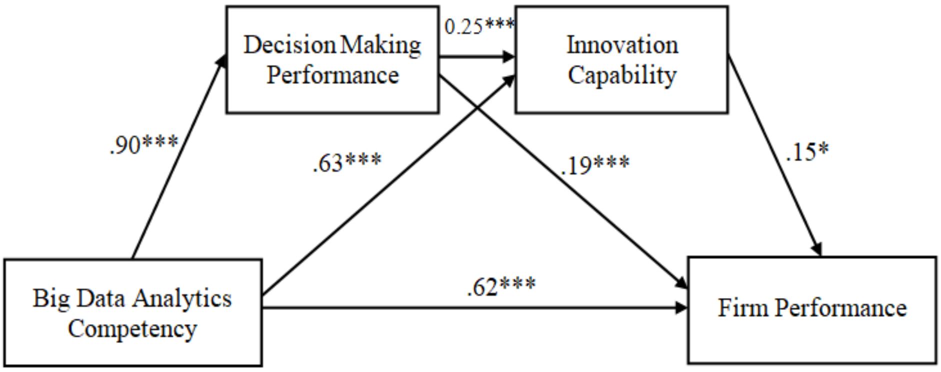

FIGURE 4.4: Model 6 for Current Study

Note: **p< .05, **p<.01, ***p<.001*

Next, Table 4.13 specifies the Total effect of BDAC on FP.

TABLE 4.13: Total Effect on FP

	Effect	**p**	**LLCI 95%**	**ULCI 95%**
BDAC	0.9362	0.0000	0.8066	1.0659

Table 4.13 indicates that total effect of BDAC through model on FP (B = 0.93, t(298) = 14.2161, p = 0.0000) which shows that effect got mediated as it is different from the direct effect of BDAC on FP. However, it has been observed that change in effect (0.3123) is not massive, therefore it is referred as partial mediation.

The indirect effects through each mediator are recorded in the next Table 4.14.

TABLE 4.14: Indirect Effect of BDAC on FP

	Effect	**BOOT LLCI**	**BOOT ULCI**
Total	0.3123	0.1783	0.4459
Ind1	0.1772	0.0738	0.2933
Ind2	0.0365	0.0033	0.0787
Ind3	0.0986	0.0049	0.2013

Note: *Ind1: BDAC → DMP → FP*
Ind2: BDAC → DMP → IC → FP
Ind3: BDAC → IC → FP
CI: Confidence Interval: 95%, Bootstrap sample size: 5000

Table 4.14 indicates that no zero value is lying between LLCI and ULCI in the 95% confidence interval through each mediation path, thus the model has got mediation effect and it leads to the validation of hypothesis $\mathbf{H_3}$ and $\mathbf{H_5}$.

4.7 Summary of Accepted and Reject Hypothesis

Based upon the computed results and their analysis, Table 4.15 below provides the precised summary of results for proposed hypothesis under current research study.

Table 4.15: Summarized Hypotheses Results

Hypothesis	Statement	Result
$\mathbf{H_1}$	Organization's competency of big data analytics has a positive and significant impact on firm performance.	**Accepted**
$\mathbf{H_2}$	Organization's competency of big data analytics has a positive and significant impact on decision making performance of a firm.	**Accepted**
$\mathbf{H_3}$	Decision making performance acts as a mediator in positive relationship between big data analytics competency and firm performance.	**Accepted**
$\mathbf{H_4}$	Organization's innovation capability has a positive and significant impact on firm performance.	**Accepted**
$\mathbf{H_5}$	Innovation capability acts as a mediator in positive relationship between big data analytics competency and firm performance.	**Accepted**

Chapter 5

Discussion and Conclusion

5.1 Discussion

Past literature has revealed that significant research have been carried in the domain of big data analytics and firm performance (Collymore et al., 2017; Maryam Ghasemaghaei et al., 2015; Raguseo & Vitari, 2018; Song et al., 2018). Moreover, studies have supported the notion that decision making performance and organization capabilities are of crucial importance to be explored and generate an impact on firm performance (Guangming & Yanqing, 2015; López-Cabarcos et al., 2015; Ringov, 2017).

Keeping in line with prior literature and findings, the major emphasis of this study was first to analyze the association between big data analytics competency and firm performance in contextual setting of Pakistan telecom and banking industry. Furthermore, the mediating role of decision making performance and innovation capability were examined in association between big data analytics competency and firm performance.

Present study suggests that there is a presence of positive and significant causal relationship between big data analytics competency and firm performance meaning that if an organization has high level of big data analytics competency, it will have high level of firm performance too. Moreover, evidences have advocated that there is a presence of positive bond between big data analytics competency and firm decision making performance which means that if an organization has high level of big data analytics competency, it will have high level of decision making performance. Additionally, results have proved that decision making performance mediates the association between big data analytics competency and firm performance as the presence of decision making performance has indicated a change in effect of big data analytics competency on firm performance. Hence this has driven the acceptance of hypotheses H_1, H_2 and H_3.

Likewise, it has been found that innovation capability is in positive and significant association with firm performance meaning that if an organization has high level of innovation capability, it will generate high firm performance; this thus made the hypothesis H_4 approved. In addition it has been analyzed that innovation capability has played the role of mediator in association between big data analytics competency and firm performance, which provides the ground for acceptance of hypothesis H_5.

The detailed discussion of each hypothesis is mentioned next.

H_1: Organization's competency of big data analytics has a positive and significant impact on firm performance.

The first hypothesis of this research predicted that an organization's big data analytics competency is in positive and significant relation with performance of a firm and result (B = 0.936, t = 14.216, p = 0.0000) has also provided the evidence for presence of association between the two mentioned variables. Moreover, the value of coefficient of determination ($R^2 = 0.404$) indicated that one unit of change in big data analytics competency can probably generate 40.4% of increase in firm performance. Big data has emerged as a new field of research in last few decades. Businesses around the globe are highly interested in realization of benefits to the fullest through their capability of BDA (J.W.Ross et al., 2013).

Literature has identified that the domain of big data analytics is still evolving and organizations are making efforts to develop such big data analytics driven capabilities which can generate a strong influence on firm performance (Akter et al., 2016;

Gupta & George, 2016). Besides, recent research has identified big data analytics competency as a producer of value in organizations as it assists them in digging insights from collected data and pro1vides them information about present and future patterns to keep them up to date and make their moves accordingly (Saggi & Jain, 2018). Additionally, numbers of research studies have explored the role of big data analytics and found that it has played a significant part in achieving competitive advantage (Kubina et al., 2015; Morabito, 2015b). And competitive advantage leads the better performance of firm by keeping them ahead of their peers. In context of Pakistan telecom and banking sector, the role of big data analytics competency is significant too as the current study has empirically validated that BDAC facilitates the high performance of firms, however organizations need to focus on multiple dimensions to develop a high level of BDAC.

H_2: Organization's competency of big data analytics has a positive and significant impact on decision making performance of a firm.

Hypothesis 2 anticipated that an organization's big data analytics competency is in strong relationship with decision making performance of a firm and result (B = 0.90, t = 11.089, p = 0.0000) has also highlighted that there is a presence of significant bond between the said variables. Also, the result of correlation coefficient (r = 0.540) supports the existence of positive relation between BDAC and decision making performance. Thus the high level of BDAC will drive the high performance of firm decision making.

Past studies have revealed that organizations are rushing towards development of strong organizational capability of big data analytics with an objective of improving their decision-making performance and that all the dimensions of BDA are acknowledged to enhance the decision quality of an organization in terms of accuracy and correctness of its outcome. Likewise all the dimensions of big data analytics are observed to improve the efficiency of organization decision in context of fast speed to reach at decision excluding bigness of data (Maryam Ghasemaghaei et al., 2018). Referring to decision making, information is the driver of quality of this process (Goes, 2014). Following the mentioned fact, big data analytics is all about extracting and providing valuable information related to needs and demands of customers, markets, suppliers and other elements which are essential to decision making. This capability of an organization helps a firm in transforming the raw data owned by organizations into meaningful information by analyzing it brilliantly and revealing the hidden insights which leads to improved decision making performance.

H_3: Decision making performance acts as a mediator in positive relationship between big data analytics competency and firm performance.

Hypothesis H_3 claimed that decision making performance plays a role of mediator in relationship between BDAC and firm performance and results ($B = 0.93$, $t(297) = 14.2161$, $p = 0.0000$) have also provided the ground for its acceptance as the direct effect of BDAC on firm performance got mediated in the presence of decision making performance. In addition, the value of LL (0.1098) and UL (0.3327) doesn't include zero between them which also endorsed the mediated effect of decision making performance in the said relationship.

Prior study have concluded that it's not only the bigness of data which drives better firm performance but it's actually how businesses develop insights from big data and exploit it to make their decision making performance better which consequently generates an impact on firm performance (Thirathon et al., 2017). Beside, a study have stressed that negligence towards insights revealed through data analytics and omitting them while decision making is one of the reasons why a firm fails in making an impact on its performance through BDA (Shah et al., 2012). The dependency of improved future performance of an organization upon its decision making performance has already been established in previous literature which claims that high quality of decisions outcome leads better performance of organization while poor quality makes bad impact on firm performance (Bolland

& Lopes, 2018). Though the mediating role of decision making performance was not explored earlier in this specific domain yet existed literature has provided the ground to explore this behavior in the mentioned association and positive results have made the proposed relation acknowledged.

H_4: Organization's innovation capability has a positive and significant impact on firm performance

Hypothesis H_4 posited that an organization's innovation capability has an association with firm performance and results (B = 0.27, t(297) = 3.9434, p = 0.0001) has proved this claim true indicating that if an organization have high innovation capability, it will have high firm performance too. In addition, the positive correlation coefficient (r = 0.557) shows that high or low innovation capability will have firm performance to move in the same high or low fashion.

Innovation has always been considered as a mean of competitive advantage and improved firm performance however innovation without innovation capability is inconceivable (Laforet, 2011; Rajapathirana & Hui, 2018). Innovation capability has been referred as one of the most significant capabilities of firm as it assists in keeping a pace with changing environment through which it generates enhanced firm performance (Breznik & Lahovnik, 2016). Existed studies have indicated that it is innovation capability which makes organization to outperform its competitors, generate higher profits and higher productivity, and increase survival probabilities subjective to gain of competitive advantage through innovation (Agbim, 2014; Al-rubaiee et al., 2015). Provided that, innovation capability has been distinguished as a differentiator tool among organizations as an organization with high innovation capability makes new moves and surmount among its competitors while posing superior firm performance (Azubuike, 2013). The results of this study for the mentioned hypothesis therefore have shown that this association between innovation capability and firm performance is also true in context of Pakistan telecom and banking industry.

H_5: Innovation capability acts as a mediator in positive relationship between big data analytics competency and firm performance.

Hypothesis H_5 proffered that an organization's capability to innovate acts as a mediator in association between BDAC and firm performance and results (B = 0.93, t(297) = 14.2161, p = 0.0000) has facilitated the mentioned hypothesis as it illustrates that direct effect of BDAC on firm performance got mediated, provided that innovation capability is present. In addition, there lies no zero in interval defined through LL (.1141) and UL (.3762) which stands the mediated effect of innovation capability in the mentioned bond.

Studies have reported big data analytics as a driver of organizational innovation and growth (OECD, 2015). Given that, extant literature in domain of organizational performance has suggested innovation as a bone of competitiveness and success in world of business (Chatzoglou & Chatzoudes, 2018). Massive observations have revealed that growing interest of organizations in adoption of big data analytics practices is due to its ability to facilitate organizational innovation through generation of useful and hidden insights (Bean, 2018). This claim is also supported by another study which mentions that today's competitive environment calls for the adoption of big data analytics to introduce innovation for high firm performance (Al-Jaafreh & Fayoumi, 2017). However in compliance to Laforet (2011), there exist no meaning of organizational innovation without concept of innovation capability. Innovation capability makes organizations capable of exploring new opportunities and introducing new products and services accordingly to satisfy customer needs, gain competitive advantage and elevate firm performance (Bowen et al., 2010; Saunila et al., 2014; Yuan et al., 2015). Thus, where highly developed big data analytics competency is a must element to analyze big data effectively and creates valuable insights, innovation capability is a must parameter to bring innovation in accordance to these driven insights and consequently improves firm performance. The results have proved this notion in context of Pakistan telecom and banking sector as results obtained for mediating role of innovation capability in relation between BDAC and firm performance are significantly positive.

5.2 Research Implications

The significant contribution made by current research has wide applicability in purview of big data analytics management and firm performance. The role offered by current study is of immense importance because no prior study has outlined the mediating behavior of decision making performance and innovation capability specifically in this context. Moreover, the integration of organizational resources which has been explored in this study to examine the big data analytics competency of a firm is not used in this combination before. Additionally, it is observed through previous studies that there is lack of literature available in domain of big data analytics regarding Pakistan organizational setting; present study thus, has made its part in bridging this gap in literature.

Findings of this study have highlighted the direct and indirect relationship between big data analytics competency and firm performance and revealed that relation between BDAC and firm performance do gets influenced by performance of firm decision making and innovation capability and that merely BDAC is not enough to generate high firm performance, which is equally important to researchers as well as practitioners because it'll draw their attention towards aspects which are of significance importance to achieve the ultimate goal of organizations through investment in big data analytics which is enhanced firm performance.

5.3 Research Limitations

Like any other research, this study possesses some specific limitations too. Firstly this study is limited only to Pakistan telecommunication and banking industry. Results may produce different outcomes for other sectors in Pakistan or for the same sector in other countries around the globe due to characteristics like size or culture of organization, etc. Secondly the sample size chosen was limited to 300 individuals only and the study was limited to analysis of cross-sectional data.

Next, present study has incorporated only few of the possible dimensions to explore big data analytics competency of an organization; while there exist probability that other dimensions can generate a strong impact too. Furthermore, this study has facilitated only two mediators in relation between big data analytics competency and firm performance. While there might be other factors which can mediate the mentioned relation however it was not possible to entertain all. Lastly, the current study has not explored the effect of any moderator in this study. It is limited to demonstrate the role of mediator only.

5.4 Future Research Directions

The domain of big data analytics needs attention of researchers as organizations are yet moving toward adoption of its practices and it is not limited to a particular area or sector. Literature has reported both the scenarios where investment in big data analytics has gain valuable returns to firms and where firms remained unable to realize the benefits of BDA. However, outcomes are subjective not only to a single factor; there can be a number of elements which makes the highly positive impact of BDA on firm performance possible.

Firstly, the current study have attempted to explore quite a number of resource dimensions which should be considered in development of strong big data analytics competency, however still there is a need to explore more IT and management related firm resources which can possibly have an effect on organization's capability of driving improvement through BDA and are not incorporated in this study. Furthermore, this study has analyzed the effect of BDAC on firm performance as a whole while researchers can explore the effect of BDAC with in specific department or area such as supply chain management etc. Additionally, the present research has examined the mediating effect of decision making performance and innovation capability in relationship between BDAC and firm performance. Future researchers can explore the moderating effect of variables like top management support, employees commitment or readiness for change in this relation.

Moreover, this research study has established the acceptance of its hypothesis based on telecom and banking sector in context of Pakistan. Research can be extended by considering the other sectors and settings too. In addition, present research is cross-sectional with regards to time interval; however as this is a capabilities based study which can draw the attention of researchers to consider longitudinal data in future to explore this relation which may provide different results.

5.5 Conclusion

This study has been carried out with an ultimate goal to explore the effect of big data analytics competency on firm performance in telecom and banking based organizations of Pakistan. Data for this study was collected from organizations who were practicing big data analytics in their organizational system (Jazz, Telenor, Zong, Ufone, Huwaie, PTCL, HBL, UBL, NBP, ABL, JS Bank, Bank Alfalah, Meezan Bank, BOP, and KMBL) through a digital survey –questionnaire to measure the degree to which big data analytics competency is posing an impact on improvement of firm performance with mediating role of decision making performance and innovation capability.

The study is based on view of Resource Based Theory that better integration and deployment of resources generates better organizational results. Firstly, it explored the integration and deployment of big data analytics specified resources which are driver of BDAC and then its influence on firm performance in telecom and banking organizations of Pakistan. Statistical tests are carried out to analyze the reliability and validity of proposed model. Additionally, different tests like correlation analysis, regression analysis and mediation analysis are performed to determine the acceptance or rejection of proposed relations. Present study has hypothesized that BDAC and firm performance are in positive association with each other and results have validated this which interprets that organizations having high level of big data analytics competency have high level of firm performance too. Next, this study has proposed that a positive association exists between BDAC and firm decision making performance and results have provided evidence for this showing that if organizations capability of big data analytics is high, their decision making performance is high too. Moreover, study has also provide ground for its another hypothesis which anticipated that innovation capability is in positive association with firm performance as results have provided the validation of this relation. Furthermore, hypotheses under this study predicted that decision making performance and innovation capability mediates the relationship between BDAC and firm performance and results have indicated that presence of decision-making performance as well as innovation capability mediated the said association. This study thus made an attempt to provide the holistic view of impact of big data analytics competency on firm performance with exploration of mediating behavior of decision making performance and innovation capability in telecom and banking sector of Pakistan.

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Appendix-A

CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY

ISLAMABAD

Department of Mechanical Engineering

Dear respondent,

I am a research scholar at Capital University of Science and Technology, Islamabad and conducting this survey as a part of my research thesis which will investigate the impact of big data analytics capability on firm performance with mediating role of decision-making performance and role of innovation capability. It would be a great favor of yours if you take 15 minutes out of your busy schedule to fill this questionnaire. These questions require answers based on your experiences in your current job. This survey is being conducted purely for a research purpose and will not be shared with anybody. Your identity will not be disclosed on this document so kindly give an honest opinion to make this research unbiased. Although you are not confined to answer these questions and you can quit answering at any point in time but still I will be privileged by your opinion in this research work. If you need findings of this research, please feel free to contact at misbaahshk@gmail.com. Thank you in anticipation for your precious time and cooperation.

Profound Regards,

Misbah Ejaz

Section-1: Demographics

Organization Name:	
Designation:	
Sector:	◯ Telecommunication ◯ Banking
Age:	◯ 20-25yrs. ◯ 26-30yrs. ◯ 31-35yrs. ◯ 36 above
Years of Experience:	◯ 0-5yrs. ◯ 6-10yrs. ◯ 11-15yrs. ◯ 16 above
Experience in Current Organization:	◯ 0-5yrs. ◯ 6-10yrs. ◯ 11-15yrs. ◯ 16above
Number of Employees in Organization:	◯ Below 50 ◯ 51-100 ◯101-150 ◯ 150 above

Section-2: Big Data Analytics Competency

It's a 7-point Likert Scale survey questionnaire and each scale holds a certain response: 1=Strongly Disagree, 2= Moderately Disagree, 3= Slightly Disagree, 4 = Neither Agree or Disagree, 5= Slightly Agree, 6= Moderately Agree, 7 = Strongly Agree

Please mark (✓) where suitable as per the above-mentioned scale.

	Data	1	2	3	4	5	6	7
BDAC1	We have access to very large, unstructured, or fast-moving data for analysis.							
BDAC2	We integrate data from multiple internal sources into a data warehouse or mart for easy access.							
BDAC3	We integrate external data with internal to facilitate high-value analysis of our business environment.							
	Bigness of Data							
BDAC4	In our organization, we process high volume of data.							
BDAC5	In our organization, we process real time data.							
	Data Quality							
BDAC6	In our organization, data used in data analytics is reliable.							
BDAC7	In our organization, data used in data analytics has an appropriate level of details.							
BDAC8	In our organization, data used in data analytics is relevant to the task at hand.							

	Technology							
BDAC9	We have explored or adopted parallel computing approaches (e.g., Hadoop) to big data processing.							
BDAC10	We have explored or adopted different data visualization tools.							
BDAC11	We have explored or adopted cloud-based services for processing data and performing analytics.							
BDAC12	We have explored or adopted new forms of databases such as Not Only SQL (NoSQL) for storing data.							
	Basic Resources							
BDAC13	Our big data analytics projects are adequately funded.							
BDAC14	Our big data analytics projects are given enough time to achieve their objectives.							
	Technical Analytics Skills							
BDAC15	We provide big data analytics training to our own employees.							
BDAC16	We hire new employees that already have the big data analytics skills.							

BDAC17	Our big data analytics staff has the right skills to accomplish their jobs successfully.							
	Managerial Skills							
BDAC18	Our big data analytics managers understand and appreciate the business needs of other functional managers, suppliers, and customers.							
BDAC19	Our big data analytics managers are able to work with functional managers, suppliers, and customers to determine opportunities that big data might bring to our business.							
BDAC20	Our big data analytics managers are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers.							
BDAC21	Our big data analytics managers have a good sense of where to apply big data.							
BDAC22	Our big data analytics managers are able to understand and evaluate the output extracted from big data.							
	Domain Knowledge							

BDAC23	In our organization, there is a high level of knowledge of the external environment (e.g., government, competitors, suppliers, and customers).							
BDAC24	In our organization, there is a high level of knowledge of the organizational goals and objectives.							
BDAC25	In our organization, there is a high level of knowledge of the core capabilities of the organization.							
BDAC26	In our organization, there is a high level of knowledge of the key factors that must go right for the organization to succeed.							
	Data-Driven Culture							
BDAC27	We are willing to override our own intuition when data contradict our viewpoints.							
BDAC28	We continuously assess and improve the business rules in response to insights extracted from data.							

Section-3: Decision Making Performance

It's a 7-point Likert Scale survey questionnaire and each scale holds a certain response: 1=Strongly Disagree, 2= Moderately Disagree, 3= Slightly Disagree, 4 = Neither Agree or Disagree, 5= Slightly Agree, 6= Moderately Agree, 7 = Strongly Agree

Please mark (✓) where suitable as per the above-mentioned scale.

	Items	1	2	3	4	5	6	7
DMP1	In our organization, decision outcomes are often reliable.							
DMP2	In our organization, decision outcomes are often precise.							
DMP3	In our organization, decision outcomes are often flawless.							
DMP4	In our organization, the time to arrive at decisions is fast.							

Section-4: Innovation Capability

It's a 7-point Likert Scale survey questionnaire and each scale holds a certain response: 1=Strongly Disagree, 2= Moderately Disagree, 3= Slightly Disagree, 4 = Neither Agree or Disagree, 5= Slightly Agree, 6= Moderately Agree, 7 = Strongly Agree

Please mark (✓) where suitable as per the above-mentioned scale.

	Items	1	2	3	4	5	6	7
IC1	Our firm has an organizational culture and a management comprehension that support and encourage innovation.							

IC2	At our firm, knowledge from different resources is used for product/service development activities efficiently and rapidly.							
IC3	Our firm is able to reflect changes at market conditions (such as changes from customer wants, competitors products, etc.) to own products and processes as soon as possible.							
IC4	Workers of our firm are supported and encouraged to participate in activities such as product development, innovation process improvement and to produce new ideas such topics.							
IC5	New ideas that come from customers, suppliers, etc. are evaluated continuously and try to include into product/service development activities.							
IC6	Our firms could adapt to environmental changes easily and in the short time by making suitable improvements and innovations at its products and processes.							

Section-5: Firm Performance

It's a 7-point Likert Scale survey questionnaire and each scale holds a certain response: 1=Strongly Disagree, 2= Moderately Disagree, 3= Slightly Disagree, 4 = Neither Agree or Disagree, 5= Slightly Agree, 6= Moderately Agree, 7 = Strongly Agree

Please mark (✓) where suitable as per the above-mentioned scale.

	Market Performance	1	2	3	4	5	6	7
FP1	We have entered new markets more quickly than our competitors.							
FP2	We have introduced new products or services into the market faster than our competitors.							
FP3	Our success rate of new products or services has been higher than our competitors.							
FP4	Our market share has exceeded that of our competitors.							
	Operational Performance	1	2	3	4	5	6	7
FP5	Our productivity has exceeded that of our competitors.							
FP6	Our profit rate has exceeded that of our competitors.							
FP7	Our return on investment (ROI) has exceeded that of our competitors.							

Thank-you for your time and cooperation!

Appendix-B

Items Code of Variables

The Table A below provides the coded keys for items of variables which were explored.

Variables	Coded Keys
Big Data Analytics Competency	
1. Data	BDAC1, BDAC2, BDAC3
2. Bigness of Data	BDAC4, BDAC5
3. Data Quality	BDAC6, BDAC7, BDAC8
4. Technology	BDAC9, BDAC10, BDAC11, BDAC12
5. Basic Resources	BDAC13, BDAC14
6. Technical Analytics Skills	BDAC15, BDAC16, BDAC17
7. Managerial Skills	BDAC18, BDAC19, BDAC20, BDAC21, BDAC22
8. Domain Knowledge	BDAC23, BDAC24, BDAC25, BDAC26
9. Data-Driven Culture	BDAC27, BDAC28
Decision Making Performance	DMP1, DMP2, DMP3, DMP4
Innovation Capability	IC1, IC2, IC3, IC4, IC5, IC6, IC7
Firm Performance	
1. Market Performance	FP1, FP2, FP3, FP4
2. Operational Performance	FP5, FP6, FP7

Appendix-C

Skewness and Kurtosis

Results of test for skewness and kurtosis of sample data are reported below in the Table.

Items	N	Statistic Skewness	Statistic Kurtosis
BDAC1	300	-0.715	-0.323
BDAC2	300	-0.916	0.943
BDAC3	300	-0.807	0.353
BDAC4	300	-0.938	0.978
BDAC5	300	-0.720	0.295
BDAC6	300	-0.905	0.749
BDAC7	300	-0.882	1.020
BDAC8	300	-0.941	0.638
BDAC9	300	-0.899	0.512
BDAC10	300	-1.254	0.952
BDAC11	300	-1.192	1.270
BDAC12	300	-0.903	0.412
BDAC13	300	-0.882	0.292
BDAC14	300	-0.724	0.020
BDAC15	300	-0.883	0.448
BDAC16	300	-1.055	1.083
BDAC17	300	-1.268	0.834
BDAC18	300	-1.117	0.560

Items	N	Statistic Skewness	Statistic Kurtosis
BDAC19	300	-1.238	0.743
BDAC20	300	-1.132	0.623
BDAC21	300	-1.056	0.909
BDAC22	300	-1.088	0.864
BDAC23	300	-1.049	1.041
BDAC24	300	-0.796	0.484
BDAC25	300	-0.924	1.138
BDAC26	300	-0.769	0.224
BDAC27	300	-1.154	1.214
BDAC28	300	-0.971	0.738
DMP1	300	-1.119	1.010
DMP2	300	-0.795	-0.135
DMP3	300	-0.702	0.322
DMP4	300	-1.03	0.647
IC1	300	-0.985	0.673
IC2	300	-1.288	0.904
IC3	300	-1.116	1.004
IC4	300	-1.092	0.76
IC5	300	-0.979	1.004
IC6	300	-0.901	0.648
FP1	300	-0.893	0.236
FP2	300	-0.692	-0.188
FP3	300	-0.728	0.410
FP4	300	-0.823	0.584
FP5	300	-0.765	0.297
FP6	300	-0.901	0.477
FP7	300	-0.677	0.099
Valid N	300		