BIG DATA IN CONSTRUCTION INDUSTRY: A MODEL OF DETERMINANTS AFFECTING THE ACQUISITION INTENTION

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Degree of Master of Science

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DECLARATION

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Name of the supervisor: Prof. A.A.D.A.J. Perera

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Abstract

Big data is defined based on 3V's namely volume, velocity, and variety. Big data is a new paradigm used for exploring and analyzing extremely large amounts of data, which can be structured, unstructured or semi structured. Due to rapid digitalization and technological revolution, construction industry is exceptionally experiencing huge amount of data. Acquisition of big data technologies and catch up with the fourth industrial revolution in construction industry remains at a nascent stage. There is a research gap on identifying the association between construction industry and acquisition intention of Big Data. This research fills the gap and proposes a model to identify the determinants affecting the acquisition intention of Big Data.

This research uses quantitative analysis of data collected from structured questionnaire targeting managers in different areas in construction industry. The data was analyzed using the partial least squares (PLS) method of applying structural equation modeling (SEM). The latest version, Smart PLS 3.3.5 was used to test the research hypotheses of the proposed model. This research identified nine core variables affecting the acquisition intention namely, absorptive capacity, data quality issues, external support, leadership focus, competitive pressure, level of awareness and understanding, perceived benefits of big data, perceived cost of big data and perceived risk of big data. Among the factors, only level of awareness and understanding has significant effect on acquisition intention of BD. Other factors have insignificant effect on acquisition intention. The possible reason for the insignificant effect of perceived benefit of BD is that the main concept and the technology are new to the respondents. Perceived benefit of BD, perceived cost of BD and perceived risk of BD was identified as the mediation variables. According to the mediation analysis, only perceived risk of BD act as mediator. Perceived benefits of BD and perceived cost of BD did not mediate the identified relationships. Finally, this research developed a model to identify the factors that affecting on acquisition intention of BD services in the construction industry.

Keywords: Big Data, Construction Industry, Innovation, Acquisition Intention

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LIST OF ABBREVIATIONS

BD	**Big Data**
BDA	**Big Data Analytics**
IoT	**Internet of Things**
AI	**Artificial Intelligence**
PLS	**Partial least squares**
SEM	**Structural Equation Modelling**
DQ	**Data Quality**
BIM	**Building Information Modeling**

CHAPTER 01: INTRODUCTION

1.1 Background

The digitalization and technological advancement have resulted in generation of extremely large amount of data every day (Chauhan et al., 2022). Large volumes of data can be collected from various sources including e-commerce sites, public sector records (Chauhan et al., 2022, scientific research publications (Maroufkhani et al., 2020), sensor networks (Yaqoob et al., 2016), Google searches (Bilal et al., 2016), online social media sites like Facebook, Twitter and Instagram (Chauhan et al., 2022).

Esteramorperez (2020) has highlighted that 2.5 quintillion (10^{18}) bytes of data is created each day. Further it explains that the digital transformations such as Internet of Things (IoT), Artificial Intelligence (AI) and Big Data Analytics (BDA) have contributed to this remarkable surge of data in recent years. A Forbes study has found some of the important statistics on data growth. It has found that more than 3.7 billion people around the world use the internet which is 7.5% of growth over the year 2016. Further it has identified that 77% of searchers are conducted on Google, which processes over 40,000 searches every second that is 3.5 billion searchers per day. Including the contribution of other search engines for the daily data generation, it has found that there are 5 billion searchers per day worldwide (Marr, 2018).

According to Domo's "Data Never Sleep 9.0" infographic, which observes the behavior of data growth and data views at every minute across top data traffic platforms and applications such as Google, Facebook, YouTube, LinkedIn etc., highlighted that 2020 pandemic turned everything upside down by increasing digitalization of daily life (Slopes, 2021). Figure 1 illustrates the increasing digitalization of daily life due to the impact of pandemic.

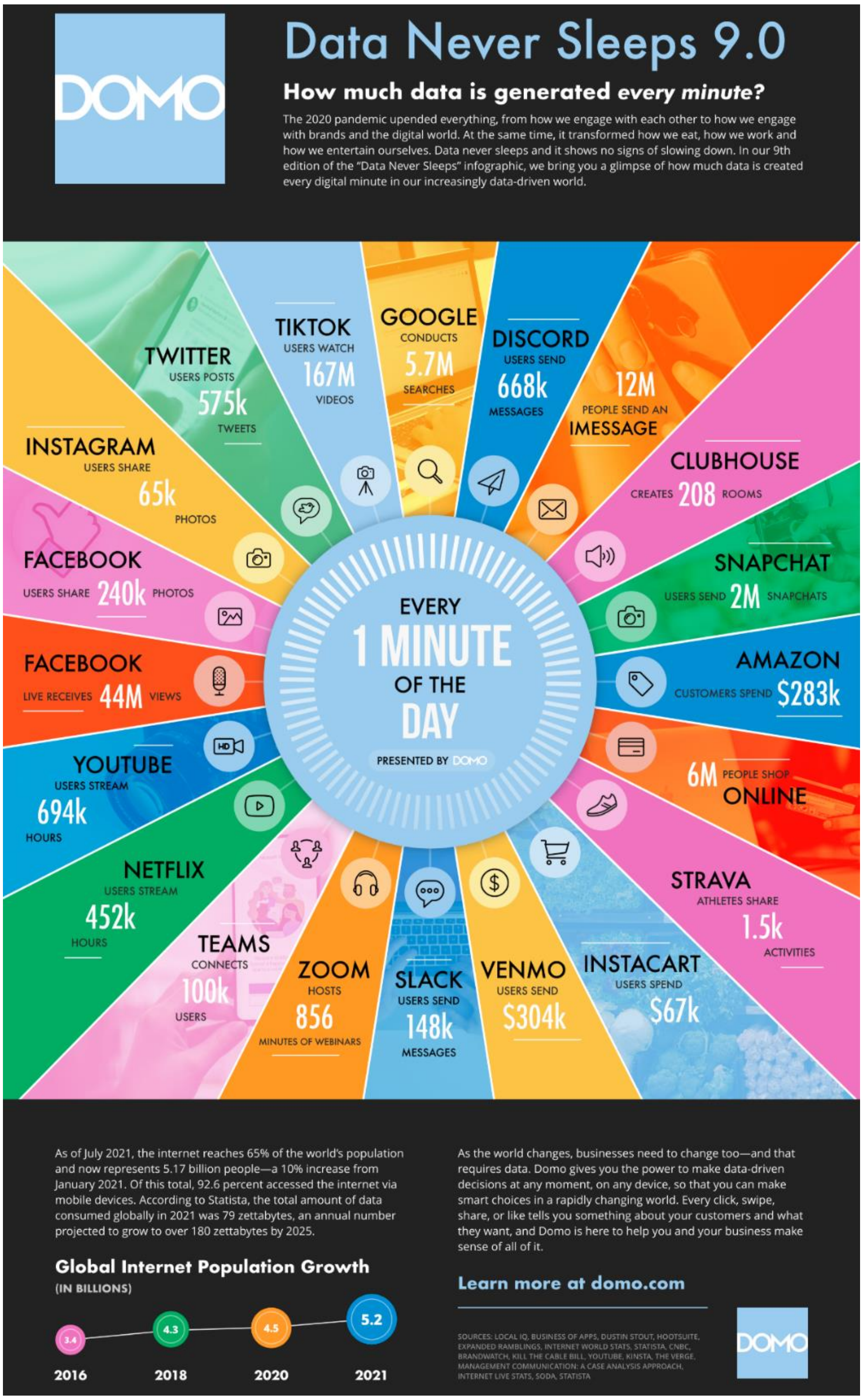


Figure 1: Data Never Sleep 9.0, behavior of data growth at every minute (Slopes, 2021)

Construction firms across the world are faced with a large pool of challenges as they continue to embrace digital transformation (Chauhan et al., 2022). Construction data is identified voluminous due to huge volume of Building Information Modeling (BIM) data, Intelligent building technology, IoT data, Building management system (BMS) data, Enterprise Resource Planning (ERP) data, planning data, design and modeling data, networking, etc. (Bilal et al., 2016). The construction organizations enter to the Big Data era due to mass gathering of construction data from different sources. (Bilal et al., 2016). According to Côrte-Real et al. (2019), BDA technologies extract big data and analyze the data with powerful analytical techniques. Figure 2 illustrates the sources of Big Data in construction industry.

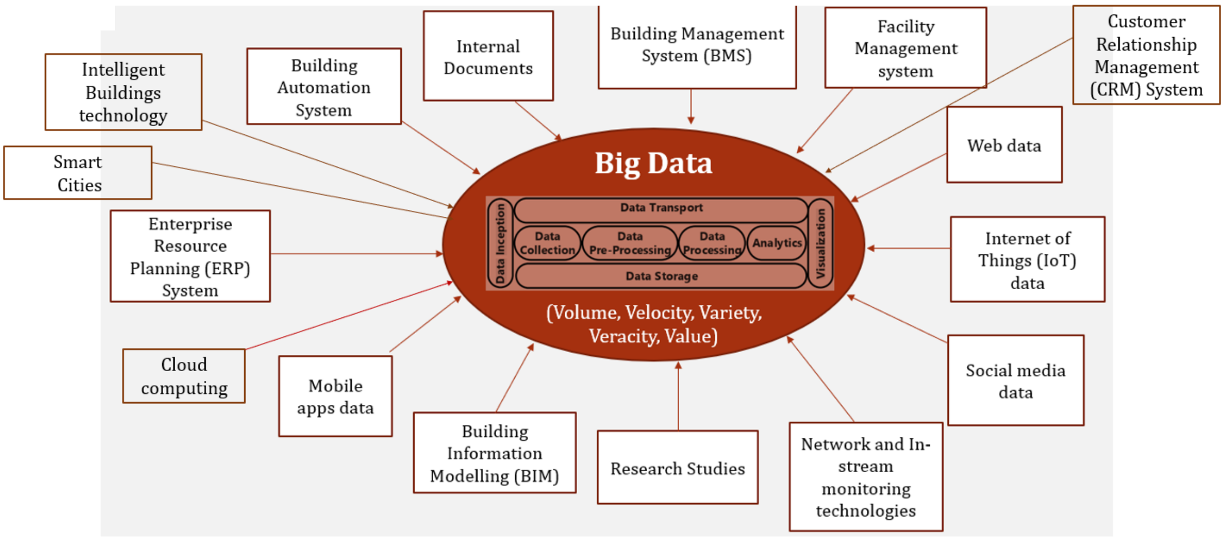


Figure 2: Sources of Big Data in construction industry

(Bilal et al., 2016; Yaqoob et al., 2016; Côrte-Real, Ruivo & Oliveira, 2019; Taleb, Serhani & Dssouli, 2018; Jha, Agi & Ngai, 2020)

The entire ecosystem within construction industry consisting of clients, contractors, consultants, and suppliers have been slow to catch up with the fourth industrial revolution (Bilal et al., 2016; Ismail et al., 2018; Woodheada et al., 2018). Evidence suggests that organizations in the construction industry are improving the industry's efficiency through adopting Big Data.

Big data is a new paradigm used for exploring and analyzing extremely large amounts of data, which can be structured, unstructured or semi structured. Big Data deals with the collection and storage of large amounts information (Bilal et al., 2016; Yaqoob et al., 2016). Big data provides large amount of information, which is not possible to collect with the traditional techniques. Big data has three V's of volume, velocity and variety (Yaqoob et al., 2016).

Maroufkhani et al. (2020) propose a model for BDA adoption using the basis of technology-organization-environment (TOE) model. This research has used the population as the SMEs in the manufacturing industry. Further the population of above has limited to the organizations that had adopted BDA already. Most of the researchers have identified the big data adoption intention for manufacturing industry (Maroufkhani et al. 2020; Vieira et al., 2020). Cabrera-Sánchez & Villarejo-Ramos (2019) have extended the UTAUT (unified theory of technology adoption and use of technology) model by including two more determinants and then altering for the concept of Big Data. Several industries have used as the population of this survey while having few responses in construction sector. Verma (2017) has conducted a research on identifying the adoption intention of BD services considering the Indian manufacturing industry. Therefore, there is a research gap to identify the determinants affecting the acquisition intention of big data applications in construction industry. There are very few literatures connecting construction industry and big data applications.

Côrte-Real et al. (2019) has identified the relationship between data quality and BDA capabilities and then assess the competitive advantage, where BDA capability acts as the mediating role of the model. Several industries such as manufacturing, retail, hotels, supply sector, mining and construction have used as the population and a multi-region survey has conducted. Percentage of the respondents from mining and construction sector has reported as 8.5% from the total respondents. Further this survey has defined based on SAP customers. Most of the literature has been focused on identifying the relationship between data quality and BDA adoption (Côrte-Real et al., 2019; Kwon et al., 2014; Vieira, 2020).

Jha et al. (2020) have identified the relationship of several variables with BDA capability in supply chain. This research has identified the factors that determine the organization's ability to build BDA capabilities. Further it has identified the mediating role of BDA capability to gain competitive advantage. Shamim et al. (2018) have evaluated the relationship between BD management barriers and challenges on BD decision making capability. Further it has examined the influence of BD decision making competence on the quality of decision. This research has done using Chinese organizations that already used BD for the organizational decision making.

Most of previous literature has been focused on technical topics. Very few literatures are based on finding the value creation and identifying competitive advantage of Big Data. Therefor there are still rich research opportunities in this area of acquisition intention of Big Data. It is important to note that most of the previous research studies are based on manufacturing industry, health sector, supply industry, retail industry etc. Most of the previous literature, BDA is context specific. There is a research gap on identifying the association between construction industry and acquisition intention of Big Data. Thus, this research contributes to extend the knowledge on BD services by identifying the factors affecting the acquisition intention. As world is moving towards digitalization, it is worth identifying the relationships on acquisition intention by construction industry.

1.2 Objectives

To propose a model to identify the factors affecting on acquisition intension of Big Data services in construction industry

1. To identify the critical factors that influence the acquisition intension of BD
2. To identify the mediating role of factors affecting on acquisition intention of BD
3. To develop a model to identify the factors that affecting on acquisition intention of BD services in the construction industry

1.3 Guide to thesis

This section identifies the chapters included in the research.

Chapter 01: Introduction provides the general information and the background of the research. Further it provides the objectives and the research requirement.

Chapter 02: Literature Review provides an in-depth review on previous research studies relevant to this research.

Chapter 03: Research methodology develops the hypotheses based on the literature review. Further it provides the proposed research model. This chapter mainly discuss about the design of the research and data collection.

Chapter 04: Data analysis chapter analyses the data obtained. It assesses both measurement model and structural model using statistical analysis software.

Chapter 05: Conclusion chapter provides the answers to the objectives. Also it provides the recommendations for the future researches.

CHAPTER 02: LITERATURE REVIEW

2.1 Introduction

This chapter provides the literature review of this research. Initially it explains the definition of Big Data. Further it explains the applications and the benefits of Big Data. Finally, it identifies the research variables by reviewing the existing literature.

2.2 Big Data

Big data is a term used for characterize the massive volume of both structured and unstructured information (Yaqoob et al., 2016), which is being collected from different sources. It has identified that these huge amounts of data are too complex to process with traditional data processing applications (Chen et al., 2020). Previous studies have defined and explained Big Data in various ways. According to the definition of Chen et al. (2020), Big Data is assets of information with high volume, velocity and variety. Further they explained that Big Data provides innovative and economical way of data processing, to strengthen decision-making, locate in-depth insight, automation, and optimization of organizational processes. Bag et al. (2020) have termed big data based on 3Vs names volume, velocity, and variety. Additionally, veracity; fourth V of Big Data was added by IBM and Microsoft while fifth V; value, was added by McKinsey & Co. to define the term Big Data (Yaqoob et al., 2016). Figure 3 illustrates the 5Vs of Big Data.

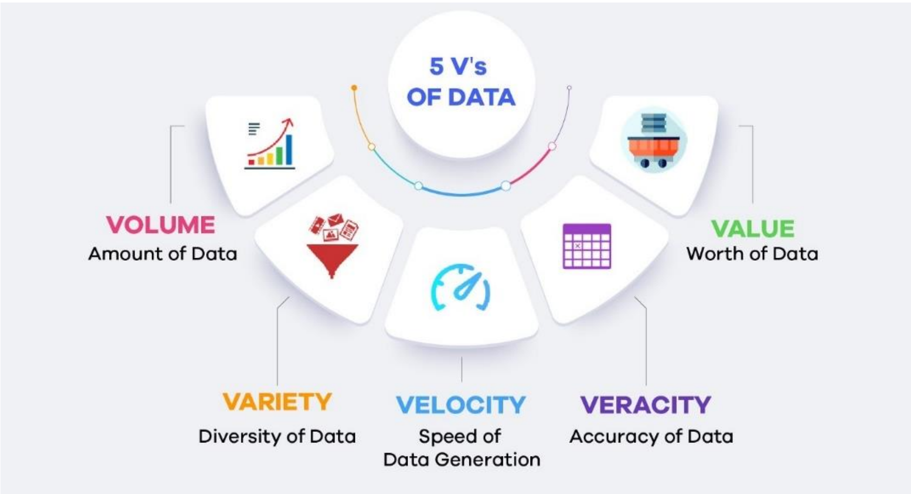


Figure 3: 5Vs of Big Data (Excelsior, 2022)

Further they have mentioned that big data refers to massive volume of structured, unstructured, and semi structured data which are generated through various data locations. Chauhan et al. (2022) has explained that in the current era of big data, the increasing demand for the accumulation and storage of these extremely large amounts of data is because of the advancement in technology and communication. Also, they have explained that huge volume of important data can be effortlessly produce and accumulate at heavy flow of data from a variety of data source. Bilal et al., (2016) have explained that big data rises from generation of different types of data, collecting it, structuring it, and finally storing it for future requirements. Big data uses a wide range of tools such as open-source software's to collect, store and analyze this large data quantity along with the help of distributed computing techniques (Gandomi & Haider, 2015). Big data is considered as an innovative concept that large amount of data is process and analyzed to produced useful information (Bilal et al., 2016). Figure 4 illustrates the concept of Big Data ecosystem.

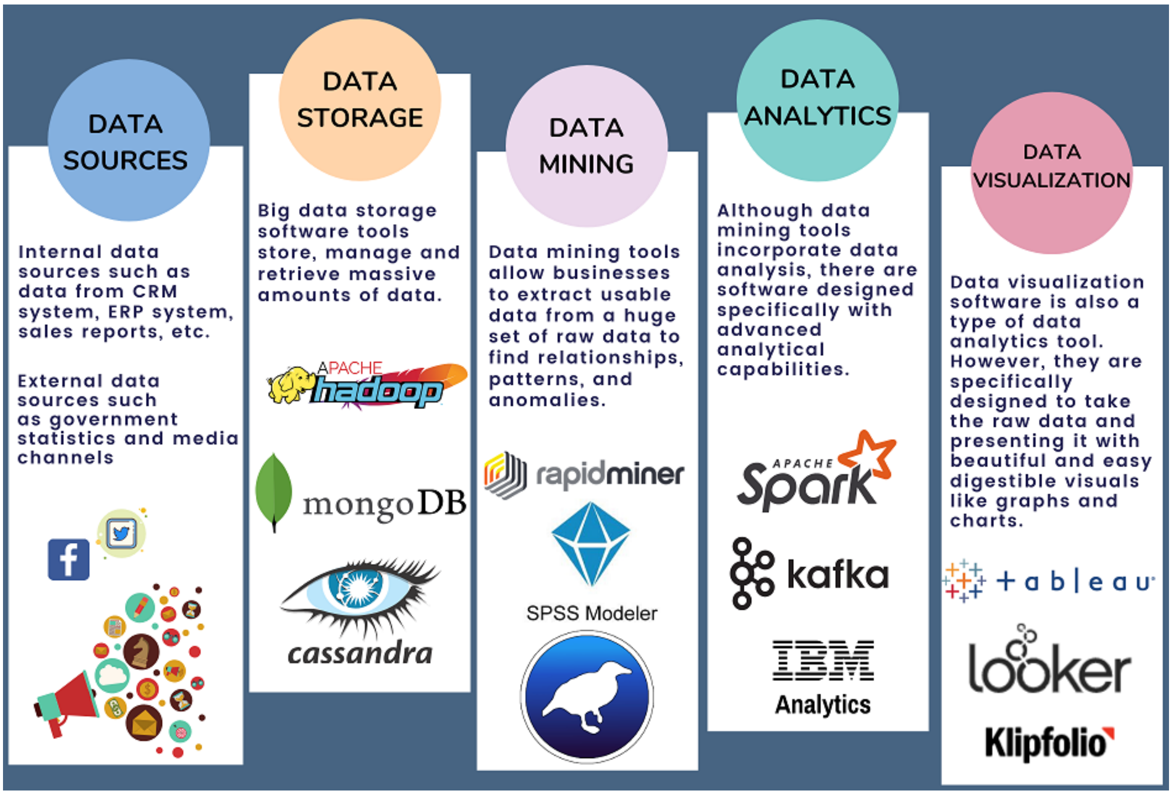


Figure 4: Big Data ecosystem (Intellspot, 2022)

According to Chauhan et al. (2022), big data is a new paradigm used for exploring and analyzing extremely large amounts of data, which can be structured, unstructured or semi structured. Further they have explained that big data deals with the collection, storage and analyze of huge amount of data, which is not possible with traditional techniques. Tokuç et al. (2019) explain that big data is a rapidly growing area that has several applications such as Big Data for supply chain management (Jha et al., 2020), Big Data for construction project management, Big Data for risk and financial modeling.

Jha et al. (2020) outlines that big data is generated by a wide range of sources and devices that have use in day to day life, such as mobile phones, tablets and social media platforms. Big data can also be gathered from non-digital devices such as electrical items, electronic items, and mechanical items by using a technology called the Internet of Things (Tokuç et al., 2019). Big Data has been rapidly developing due to its potential multimedia applications in fields such as business, science, and medicine (Jha et al., 2020). Big Data technology has been adopted in several industries such as telecommunications, banking, stock market trading and online social networks (Bilal et al., 2016).

Big Data is analyzed using BDA, which provides real time information and intelligence to the organizations about various parameters such as customer preference, sales performance etc. (Bilal et al., 2016). BDA extract hidden data patterns from a set of raw information. Then it is used for accurate decision making, increase productivity, cost reduction, knowledge generation and upgrade innovation (Maroufkhani et al., 2020). Previous studies have found that organizations get highly beneficial from BDA adoption as it improves organizational performance in every possible way (Bag et al., 2020; Bilal et al., 2016, Chauhan et al., 2022; Gandomi & Haider, 2015; Maroufkhani et al., 2020; Tokuç et al., 2019)

2.3 Benefits and usage of Big Data

As per the previous literature, there are several benefits and objectives of big data. Big data provides a larger view that helps in creating business opportunities, improving customer experience, and creating competitive advantage for the involved organizations (Ajah & Nweke, 2019). Jha et al. (2020) and Maroufkhani et al. (2020) outlines big data as most extreme transition in technology because of its potential in accurate and faster decision making (i.e., supply chains), providing in depth insights (i.e., operations), identifying customer requirements and experiences (i.e., sales), predictions on risk and opportunities (i.e., finance), making emotional and rational decisions (i.e., marketing) and stakeholder and employee analysis (i.e., HR and project management).

Big data helps in providing real time information and intelligence to the organizations (Jha et al., 2020). As explain by Chauhan et al. (2022), cloud computing and Hadoop distributed file system provides large amount of space for storage in big data storage system. Thus, it allows organizations to store all the generated data throughout the lifecycle. Bilal et al. (2016) explains that big data helps in accurate and fast decision making which reduce time and increase efficiency of organizational process management. Further they have shown that finding patterns, correlations and forecasting future events by recognizing hidden relationships among Big Data, enables companies to improve their products and services. Also, they have discussed the benefits the construction industry is getting in taking important business decisions such as making marketing and sales strategies, estimating profit and loss, managing risk and financial modeling etc. With regard to organizational decision making, big data aids in improving quality of decision-making process by streamlining the process (Yaqoob et al., 2016). Big data is helpful for construction managers to support their business growth by providing them with insights for taking correct decisions (Maroufkhani et al., 2020). These series of innovations support construction industry for their business growth by providing them with insights for taking correct decisions and opportunities. According to the research done by Ajah & Nweke (2019), big data assist in effective risk management. Further it explains that the use of big data ensures reduction in risks and costs is done through identification of potential issues during design stage itself which helps reduce human error later. Figure 5 illustrates benefits of Big Data in general.

Figure 5: Big Data benefits (Farmer, 2022)

Bilal et al. (2016) explain that due to rapid digitalization and technological revolution, construction organizations are exceptionally experiencing heterogenous amount of data. Building information modelling (BIM), Artificial Intelligence (AI), building management systems (BMS), intelligent building technology, Enterprise resource planning (ERP) systems, internet of things (IoT), cloud computing, smart building, augmented reality (AR), virtual reality (VR) and social networking services are identified as some of the main constituents that trigger big data in the construction industry (Ismail et al., 2018).

According to literature construction industry specifically benefited from Big Data as the bulk of construction data allows the development of reliable construction models (Yaqoob et al., 2016). Further Big Data preprocessing techniques ensure the accuracy and validity of construction data and identify the usefulness of big data. Big data enables different construction management models which vary in accordance with big data sources. (Chauhan et al., 2022)

2.4 Previous models developed for technology adoption

As technology adoption is crucial for business process development and profit optimization, several technology adoptions models have been developed by researchers and tested for real scenarios. Three main technology adoption models were identified from the literature: 1. theory of planned behavior (TPB), 2. technology adoption model (TAM) and 3. Unified theory of acceptance and use of technology model (UTAUT) (Sancho-Zamora et al., 2021).

Figure 6 represents the theory of planned behavior which forecast the individual determination to take part in a behavior. Researchers have identified numerous limitations of this model and mainly incompetence to examine environmental and economic influences has been identified one of the main limitations.

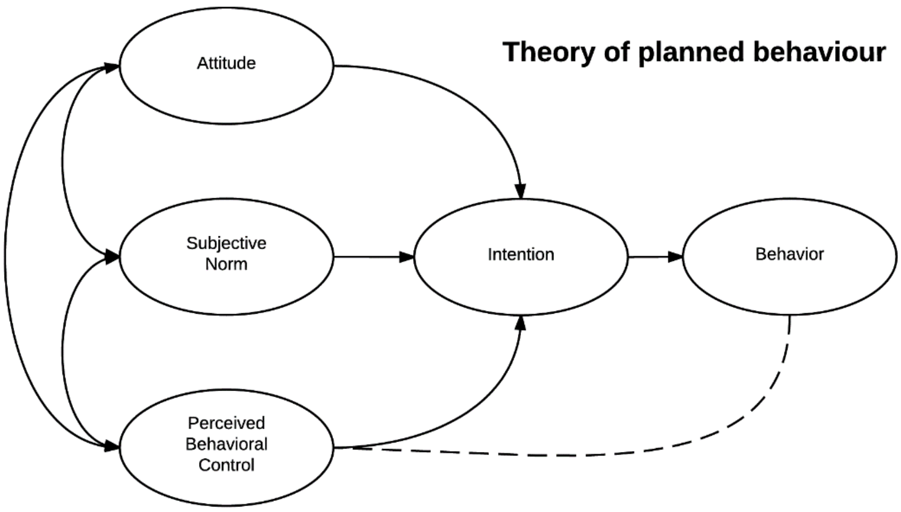


Figure 6: Theory of planned behavior (TPB) (Octav-Ionut, 2015)

Figure 7 illustrates the Technology adoption model (TAM) which is developed and tested to assess the adoption of new technology based on personal attitudes. According to TAM, perceived usefulness and perceived ease of use are the main two attitude measures that leads to new technology adoption (Allen, 2020).

Researchers have extendedly developed models based on TPB and TAM by expanding with more variable and creating complicated versions.

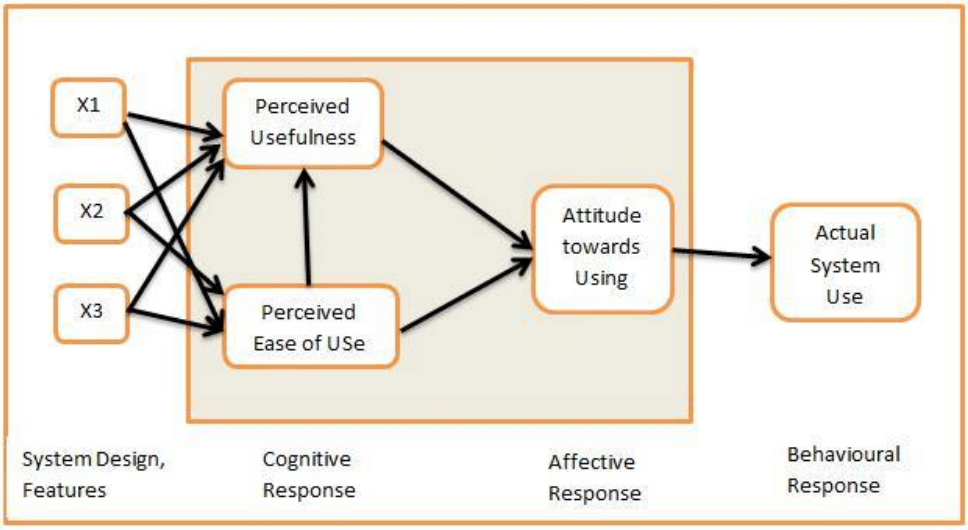


Figure 7: Technology adoption model (TAM) (Banissi et al., 2019)

Figure 8 represents the unified theory of acceptance and use of technology model (UTAUT) has identified as one particular compressive model that use to identify the user intention to use new technologies.

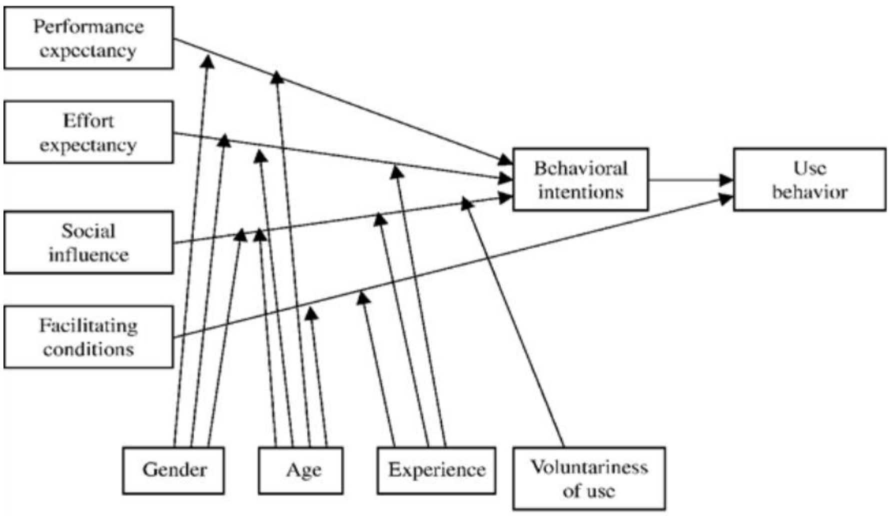


Figure 8: Unified theory of acceptance and use of technology model (UTAUT)

This research introduced an integrated research model based on TPB, TAM and UTAUT by introducing identified variables and relationships.

2.5 Present research variables

Literature review was conducted to identify the factors affecting the acquisition intention of BD. Table 1 shows the summary of independent variables identified using key research articles.

Table 1: Literature review on independent variables

	Focus area (Dependent variable)	**Factors (Independent variables)**	**Method of Data Collection**	**Reference**
1.	Big Data Analytics (BDA) adoption	Relative advantage, Complexity, Uncertainty, and insecurity, Trialability, Organizational readiness, Top management support, High degree of regulatory, Competitive pressure, Compatibility	Questionnaire Survey of 171 SMEs respondents in Manufacturing sector	Maroufkhani et al. (2020)
2	BDA capabilities and IOT capabilities	Data Quality, process sophistication, Process information intensity, process complexity	Questionnaire Survey of 618 respo. SAP customers	Côrte-Realet al. (2019)
3	BDA capability	Data management and use of advanced software, Human resource and training, Organizational politics, Global integration, Environmental determinism	semi-structured open-ended 14 interviews	Jha et al. (2020)
4	Big Data decision making competency	Leadership focus, Talent management for Big Data, Technology, Organizational culture	86 structured questionnaires in Chinese firms	Shamim et al. (2018)

	Focus area (Dependent variable)	Factors (Independent variables)	Method of Data Collection	Reference
5	Intention to adopt Big Data services	Big data quality, Absorptive capacity, Perceived benefits, Perceived cost	Questionnaire Survey with 205 responses	Verma (2017)
6	Acquisition intension of BDA	Significance of data consistency, Significance of data completeness, Perceived benefits of external data usage and internal data usage, Resource enabling condition	Survey with 306 responses	Kwon et al. (2014)
7	Adoption of Big Data Analytics	Perceived Risk, Resistance to use, Performance expectancy, social influence, Facilitating conditions	199 responses of CEOs and managers	Cabrera-Sánchez & Villarejo-Ramos, 2019

This research has identified nine main variables for the research model: organizational absorptive capacity, organizational data quality issues, external support, leadership focus, competitive pressure, level of awareness and understanding, perceived benefits of big data, perceived cost of big data and perceived risk of big data services. Chapter 03 explains each variable broadly using existing literature.

2.6 Theoretical Background

The following subsections provide an outline of the determinants that effect on the acquisition intention of big data.

2.6.1 Absorptive capacity

As the world is dealing with the knowledge economy era, organizations demand high level of knowledge (Sancho-Zamora et al., 2021) and that has identified as one of the important resources. According to the previous studies, need of organizational absorptive capacity has never been greater than now. Organizations cannot depend solely on different external knowledge such as outsourcing. Therefore, organizations have to possess and grow their absorptive capacity in order to actively absorb knowledge (Sancho-Zamora et al., 2021). This requirement facilitates learning and absorbing thus enables the organization to make use of the knowledge with innovation (Ibarra-Cisneros & Her0nández-Perlines, 2020). It has identified that absorptive capacity is essential to an organization for innovation and to gain competitive edge (Chen et al., 2009). Consequently, absorptive capacity of the organizational is foremost for value addition within the organization (Sancho-Zamora et al., 2021).

In accordance with previous studies, absorptive capacity has been defined as the ability of an organization to identify the importance of modern information and utilize it for business purposes (Sancho-Zamora et al., 2021). Griffith et al. (2003) highlight the ability of employees to assimilate available knowledge is the absorptive capacity of the organization. Sancho-Zamora et al. (2021) outlines absorptive capacity is important in the knowledge management process.

Sancho-Zamora et al. (2021) assert that organizational performance is measured based on the knowledge it possesses. Therefore, knowledge is identified as a strategic resource which acknowledges organizational innovation (Ibarra-Cisneros & Her0nández-Perlines, 2020). Acquisition of information externally is identified as one of ways to produce organizational knowledge. Consequently, it has recognized that absorptive capacity of knowledge is one of the important factors for value creation within the organization (Sancho-Zamora et al., 2021). Further, Sancho-Zamora et al. (2021) reveals the need for absorptive capacity as an important factor in knowledge transfer. Furthermore, it highlights that when firms do not have enough resources or abilities to absorb new technology, it will be difficult, if not impossible for them reach a high level of performance and productivity.

2.6.2 Organizational data quality

Many researchers have defined data quality as fitness for use (Brohi et al., 2016; Silvola et al., 2016; Zong et al., 2019). According to literature, data quality can be seen as a spectrum, with both high and low degrees of satisfaction. In some cases, users will have no problems using the data while in others it may cause them significant issues which depend largely on how that specific person handles information (Silvola et al., 2016).

Revolutionizing era of big data resulted in huge scale data generation, data storage, data integration and data analysis. Among all the other determinants, data quality has been identified as the most predominant determinant when consider in effective as well as result-oriented analysis (Brohi et al., 2016). Further the previous literatures highlight the importance of data quality as compromised quality of data can result poor decision making (Yaqoob et al., 2016). As stated by Brohi et al. (2016) poor data quality has cost approximately 600 billion dollars annually to US businesses in 2016 which shows that poor data quality is costly to the organization.

2.6.3 External support

External support from vendors is identified as to the extended support and assistance which is given by a third party to encourage organizations for adoption of innovation (Gangwar, 2018). Innovation can be a tough task for some organizations especially when they lack the key resources and expertise that is crucial for successful implementation. Thus, external support from vendors have identified as one of the important determinants that should consider when adopting innovation.

Support of vendors is crucial as it provide organizations with access to knowledge on innovation, as vendors have already been through all the possible circumstances (Maroufkhani et al., 2020).

2.6.4 Leadership focus

Top management support or the leadership focus has been considered as an attribute of this research that affect acquisition of big data. Management support has been identified as the level to which top managers understand and accept the innovation competencies of a front-line technology such as BD (Maroufkhani et al., 2020). Many studies have identified that leadership focus is a crucial factor of successful innovation adoption (Chen et al., 2015; Shamim et al., 2018; Cruz-Jesus et al., 2019; Maroufkhani et al., 2020). Top managers was identified as the main decision makers of an organization, thus their support act as a main attribute of acquisition intention of innovation (Maroufkhani et al., 2020). Further researchers have explained that the need and utilization of big data does not replace the requirement of human guidance and leadership as human insight is crucial for decision making (McAfee, 2012).

Shamim et al. (2018) has revealed that leaders act an important role in directing the organizational staff in an effective way towards innovation. Consequently, knowledge management is an important factor that requires management attention which positively influences an organization. Shamim et al. (2018) has investigated the relationship of ability to make BD decision on leadership focus. Also, explained that leadership is a strategic factor which encourages organization to generate innovation by guiding and implementing strategies. Many researchers have argued that big data environment is an interesting area for managers as it represents AI, which is powered by big data (Shamim et al., 2018).

2.6.5 Competitive pressure

Competitive pressure has identified as an external environmental factor that organization tackles with their external boundaries (Maroufkhani et al., 2020). And further it has shown that competitive pressure is an element that influences organizations acquisition of big data. Chen et al. (2015) has defined competitive pressure as external environmental influence that causes the organization to use big data analytics. Maroufkhani et al. (2020) have explained the competitive pressure as the pressure and force which comes to an organization from the external stakeholders such as customers, suppliers, and competitors.

2.6.6 Level of awareness and understanding

In the big data era, it is important for firms to be able to accept the new technology and to integrate knowledge from different databases. Previous researchers have shown that the awareness and understanding level of knowledge from different sources enhance the capability for successful decision making (Izhar & Shoid, 2016).

Acquisition of BD is important to organizations as it generate more accurate data analysis which leads to accurate and confident decision making. Researchers have highlighted the importance of taking the maximum advantage of BD opportunities. Further they have highlighted the importance of effective data storage to ensure the reliability and effectiveness of raw data. Once the data is stored among relevant databases, the organization should be capable in identifying, extracting, assembling, and analyzing data effectively for decision making (Izhar & Shoid, 2016).

2.6.7 Perceived risk of big data

Bilal et al. (2016) have explained the data security and data privacy as the pitfalls of BD in construction industry. Among the perceived risk factors, they have highlighted that data security; data ownership and data management are prominent concerns. To overcome these issues many studies have identified several security measures for the implementation such as access control, intrusion prevention, DoS (denial of service) prevention etc. (Elragal, 2014; Bilal et al., 2016). Further they have mentioned that issues related to perceived risk of big data requires more in-depth studies considering BIM related constructed data buy providing relevant solutions.

Brohi et al. (2016) have explained that big data service providers need to secure both their infrastructure and the service proving method. Data security has identified as one of the predominant determinants of perceived risk of big data. Organizations mostly concerning about maintain the databases confidentially. As big data extracted from multiple different sources including IoT and stored using cloud computing, this has various security concerns (Maroufkhani et al., 2020).

Most of the times organizations outsources the big data services not only to get the maximum benefit of the technology but also due to lack of skills, experts, and technology. From the perspective of outsourcing, the perceived risk is still act as an important determinant which needs to consider (Maroufkhani et al., 2020). Further the studies have shown the risk of outsourcing such as losing the control of the data and information. Thus, this research believes that the factor of perceived risk of big data is influential for the acquisition of big data.

2.6.8 Perceived benefits of big data

Previous studies have defined perceive benefit as an advantageous and superior result which strengthen the self-efficacy or that provide values. Further they have explained that perceived benefits are the benefits which make easier things to achieve superior values and goals (Verma, 2017). Many researchers (Kwon et al., 2014; Verma, 2017) have explained the perceived benefit in respect of economic profitability, reduction of cost, time saving and effort saving.

One of the main advantages that can be identified of big data analytics is it is designed to process heterogeneous and informal data from multiple different sources, while conventional BI technologies (ERP databases) mainly utilize data from formal and internal data sources (Kwon et al., 2014). Further Kwon et al. (2014) have explained that big data extract data beyond internal data sources which also includes data from sensors, networking data etc. Considering the above discussion, this study identifies the relationship of perceived benefit of BD on acquisition intention.

2.6.9 Perceived cost of big data

Perceived cost has identified as one of the aspects of organizational readiness that have to be sustain when adopting innovation. Verma (2017) has explained that perceived cost consists with two main sources named financial investments and administrative costs. Further it has explained that financial cost incurred in the acquisition process includes initial setup cost, operational cost, and cost of training. Moreover, the additional types of costs that arouse during the acquisition process are associate to the administrative costs and implementation costs (Verma, 2017).

Maroufkhani et al. (2020) have highlighted that every technological innovation incurs considerable of cost for implementation process. Further they have shown that set up data centers and purchase licenses for software is important investments for organization. According to the previous studies (Bilal et al., 2016; Verma, 2017; Sivarajah, 2017; Maroufkhani et al., 2020) cost of subject experts and skilled IT employees is another overhead which need to be considered as a perceived cost. Further they have highlighted that these perceived costs are important to keep the entire process running.

Bilal et al. (2016) have explained that introducing costly technologies to construction projects are more likely to be opposed as well as difficult considering the low profit margin. Even so they have argued that Big Data has the potential and ability to increase the project deliverables by optimizing the project processes and lessening risks. It has explained the importance of these innovations as construction organizations usually experience delays, litigations, lack of resources, etc. Previous studies (Bilal et al., 2016; Sivarajah, 2017; Maroufkhani et al., 2020) have outlined that construction industry can acquire huge profit from acquisition and implementation of Big Data as experienced by other industries. Moreover, they have explained the importance of using the correct methodology to implement Big Data to gain optimum benefits.

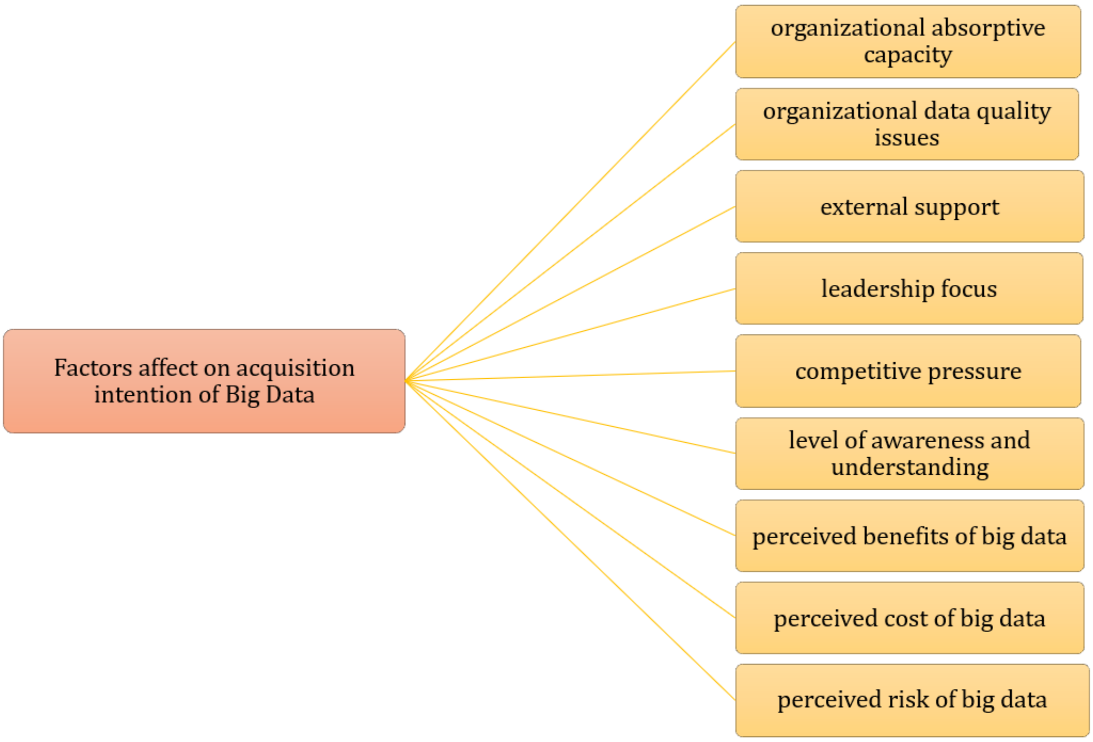


Figure 9: Research variables

2.7 Summary

Big Data is defined using 3Vs namely volume, velocity, and variety. Whereas, volume is identified as the size of the data, velocity is identified as speed of data movement and variety is identified as different or diversity of data. These 3Vs of Big Data are clearly understood in construction data due to its heterogeneous and dynamic characteristics. Finally absorptive capacity, data quality, external support, leadership focus, competitive pressure, level of awareness, perceived benefit, perceived cost, and perceived risk has identified as the nine core variables of this research.

CHAPTER 03: RESEARCH METHODOLOGY

3.1 Introduction

This chapter identifies the methodology of this research. Initially it discusses about the measurements considered when designing the research. Further, it explains about the questionnaire development. Mainly this chapter highlights the method of sampling and data collection with also tabulating the general information of respondents. And then it concludes explaining the data analysis technique.

3.2 Selection of research methodology

Table 2 represents the summary of the research methodologies used by previous researchers. Based on the summary this research uses quantitative techniques using hypothesis testing as the research methodology of this research.

Table 2: Research methodology selection

	Technology adoption (Dependent variable)	**Research methodology**	**Method of Data Collection**	Author
1.	Big Data Analytics (BDA) adoption	Quantitative analysis - Hypothesis testing	Questionnaire Survey of 171 SMEs respondents in Manufacturing sector	Maroufkhani et al., 2020
2	BDA capabilities and IOT capabilities	Quantitative analysis - Hypothesis testing	Questionnaire Survey of 618 respo. SAP customers	Côrte-Realet al., 2019
3	BDA capability	Qualitative analysis - Thematic analysis	Semi-structured open-ended 14 interviews	Jha et al., 2020
4	Big Data decision making capability	Quantitative analysis - Hypothesis testing	Structured questionnaires of 86 respo. in Chinese firms	Shamim et al., 2018
5	Intention to adopt Big Data services	Quantitative analysis - Hypothesis testing	Questionnaire Survey with 205 responses	Verma, 2017

	Technology adoption (Dependent variable)	**Research methodology**	**Method of Data Collection**	Author
6	Acquisition intension of Big Data Analytics	Quantitative analysis - Hypothesis testing	Survey with 306 responses	Kwon et al., 2014
7	Adoption of Big Data Analytics	Quantitative analysis - Hypothesis testing	199 responses of CEOs and managers	Cabrera-Sánchez | Ángel F. Villarejo-Ramos, 2019

3.3 Hypotheses Development

3.3.1 Absorptive Capacity

Chen et al. (2009) & Verma (2017) outline the importance of absorptive capacity of an organization that influences innovation, financial outcomes, and competitive advantage. As mentioned by Sancho-Zamora et al. (2021), absorptive capacity of external knowledge should be considered as an essential factor for the technological innovation in organizations which enable to adapt with competitive environment. Verma (2017) has found that absorptive capacity is one of the critical factors for the innovativeness of the organization.

Previous studies on innovation have described the absorptive capacity as a pre requirement for rapid innovation and adaptable organizational reaction (Verma, 2017; Sancho-Zamora et al., 2021). Verma (2017) has highlighted that adoption of BD services is impossible, unless the end users are capable in identifying unique and appropriate methods to extract the required knowledge. Further it has identified that this includes integrating the structured and unstructured data from various sources. Thus, absorptive capacity has been identified as one of the critical factors affect in acquisition of big data services. Many researchers have argued that, leveraging big data services highly requires experts with domain knowledge, potential of identifying the opportunities for growth and acting on innovative in-depth insights (Verma, 2017; Shamim et al., 2018; Jha et al., 2020; Shabbir & Gardezi, 2020; Sancho-Zamora et al., 2021). In consideration of above arguments, following hypotheses are proposed for the model.

H1. Absorptive capacity is positively associated with perceived benefits of BD

H2. Absorptive capacity is positively associated with acquisition intention of BD

3.3.2 Organizational data quality

Most of the modern data-oriented systems integrate data, processes, and modules of an organization into a central database (Elragal, 2014). Poor Data Quality (DQ) has been recognized as one of the major factors affecting modern system failure. Thus, it has prevented users from using the modern data-oriented systems (Xu et al., 2002). Zong et al. (2019) reveals that poor data quality adversely impacts business revenue, productivity, competitive advantage, decision-making process, and financial performance of the company (Sivarajah et al., 2017). Integrating data-oriented systems with big data analytics has identified as a major benefit to organizations as it collaborates to use all the data available in the databases to gain valuable insight. Otherwise, the researchers have shown that, most of the data generated by the modern systems is neglected (Elragal, 2014).

Bilal et al. (2016) has highlighted that construction industry is popular for fragmented data management practices. Côrte-Real et al. (2019) has explained that organization can gain the competitive advantage using big data services only if the construction data have a considerable level of quality. Further they have argued that construction industry can improve the confidence of the outputs of decision-making process, only if it uses good quality raw data.

Verma, (2017) has rationalized that high quality level of data is a valuable asset which improves revenue and profits, increase customer satisfaction and offer a strategic competitive advantage. Previous studies have explained that data quality as a multidimensional concept (Zong et al., 2019). Following hypotheses were formulated considering the above discussion.

H3: Data Quality issues in the organization is positively associated with perceived benefits of BD

H4: Data Quality issues in the organization is positively associated with perceived cost of BD

H5: Data Quality issues in the organization is positively associated with acquisition intention of BD

3.3.3 External support

Ghobakhloo (2011) has explained that external support is one of the critical drivers for the success of innovation. Further it has mentioned that innovation adoption can positively influence by external support. According to Gangwar (2018), receiving the support from vendors is a considerable attribute for the adoption of BDA. Further it has explained that organizations can develop the organizational innovation capabilities by acquiring the knowledge from vendors.

Maroufkhani et al. (2020) explained that outsourcing from vendors or external stakeholders works extremely beneficial for SMEs, especially when sufficient technical skills is lack for adoption of innovation such as big data analytics. Based on this approach, the research study develops the following hypothesis

H6: External support is positively associated with acquisition intention of big data

3.3.4 Leadership focus

Maroufkhani et al. (2020) mention decision and support of leaders are important for the adoption of innovation. Further they have highlighted that leader's innovativeness related to the tendency for innovation adoption. Furthermore, it has showed that leaders are the main connectors between organization and technology adoption. Shamim et al. (2018) have explained that the way managers address, outline, and communicate innovation affect the resources and decision making. Moreover, they have argued that management planning, attention, resource allocation and control is vital for rapid evolution of innovation. Researchers have showed that addressing management related challenges related to innovation such as big data, begins with leadership focus (Shamim et al., 2018; Cruz-Jesus et al., 2019; Maroufkhani et al., 2020). In the big data era, researchers have stated that organizations are successful mainly due to strategic management vision and clear set of goals. Thus, following hypothesis is proposed for the research based on above literature.

H7: Leadership focus is positively associated with acquisition intention of BD

3.3.5 Competitive pressure

Asiaei & Rahim (2019) have revealed that the organizations are working under pressure to compete by expecting to adopt new technologies successfully. Maroufkhani et al. (2020) explained that competitive pressure significantly influences the innovation adoption in organizations. Previous studies believed that usage of innovation by competitors could inspire the top management to successfully utilize modern technologies to uphold the organizations position in the market (Chen et al., 2015; Maroufkhani et al., 2020)

As explained by Jha et al. (2020), competitive pressure is one of the main consequences which lead to investments in technological and capability development in organizations. Further it explained that most of the companies adopt modern technologies to stay competitive and retain the clients. Also, it explains that this type of competition can be seen especially when the organizations faced high competition due to their competitor’s innovation adoption (Jha et al., 2020). In line with above discussion, this research identifies the relationships of competitive pressure using following hypotheses.

H8: Competitive pressure is positively associated with perceived cost of BD

H9: Competitive pressure is positively associated with acquisition intention of BD

H10: Competitive pressure is positively associated with perceived risk of BD

3.3.6 Level of awareness and understanding

To go through the data analyzing process starting from identifying relevant data, is a challenge for an organization (Izhar & Shoid, 2016). Researchers have highlighted that organizations should be aware on the technological processes to gain the real advantage (Tennakoon & Lasanthika, 2020). Therefore, having an understanding and awareness on big data is important to ensure competitive advantage and for effective decision making (Izhar & Shoid, 2016; Tennakoon & Lasanthika, 2020). Considering the above discussion following hypotheses were generated.

H11: Level of awareness is negatively associated with perceived cost of BD

H12: Level of awareness is positively associated with acquisition intention of BD

H13: Level of awareness is negatively associated with perceived risk of BD

3.3.7 Perceived risk of big data

Previous studies have shown that adoption of innovation can accompany uncertainty which is considered as a perceived risk (Ghasemaghaei, 2020, Maroufkhani et al., 2020). Further they have highlighted that the perceived risks act as a barrier for acquisition of modern technologies. It has identified that the organizations mostly concern on data security and data privacy before adopting data relation innovation (Maroufkhani et al., 2020).

Recent studies on acquisition of innovation have also explained the significance of concerning on perceived risk of big data (Brohi et al., 2016; Sivarajah et al., 2017; Raguseo & Vitari, 2018; Cabrera-Sánchez, 2019; Ghasemaghaei, 2020; Maroufkhani et al., 2020). Further they have highlighted the importance of identifying how it effects on acquisition intention. As stated by Maroufkhani et al. (2020), security and privacy issues are directly linked with BD as the cloud computing is a host for data. Perceived risk is also linked with adoption of big data due to the use of third-party tools and assistance (Maroufkhani et al., 2020).

Therefore, the following hypotheses are proposed for the research.

H14: Perceived risk of BD is positively associated with perceived cost of BD

H17: Perceived risk of BD is positively associated with acquisition intention of BD

3.3.8 Perceived benefits of big data

Maroufkhani et al. (2020) have explained it as the extent to which the acquisition of innovation is perceived as superior when consider the other possible innovation and benefits it provide to the organization. As explained by Kwon et al. (2014), perceived benefit is one of the best predictors for the acquisition of innovation. Further they have explained that successful experience with previous innovation projects may strengthen an organizations intention to acquire other technological innovation. That logic has also explained as accomplishing goals with past projects lessening the uncertainties about the latest innovation (Kwon et al., 2014)

H15: Perceived benefits of big data is positively associated with acquisition intention of BD

3.3.9 Perceived cost of big data

Previous studies have highlighted that higher perceived cost of innovation would lead to lower the acquisition intention (Verma, 2017; Maroufkhani et al., 2020). Sivarajah

(2017) has outlined that BD service equally creating opportunities to organizations and challengers to stakeholders. Among all the challenges, high initial investment cost for implementation and operational cost could prevent organizations from acquisition of innovation (Sivarajah, 2017). Researchers (Verma, 2017; Sivarajah, 2017; Maroufkhani et al., 2020) have identified the implementation costs includes the cost of relevant software, cost of IT infrastructure, cost for initial set up, operational cost, training cost, security and privacy cost.

H16: Perceived cost of big data is positively associated with acquisition intention of BD

3.4 Proposed research model

Our proposed model (See Figure 10) includes nine variables which has identify by the literature review. They are organizational absorptive capacity, organizational data quality issues, external support, leadership focus, competitive pressure, level of awareness and understanding, perceived benefits of big data, perceived cost of big data and perceived risk of big data services.

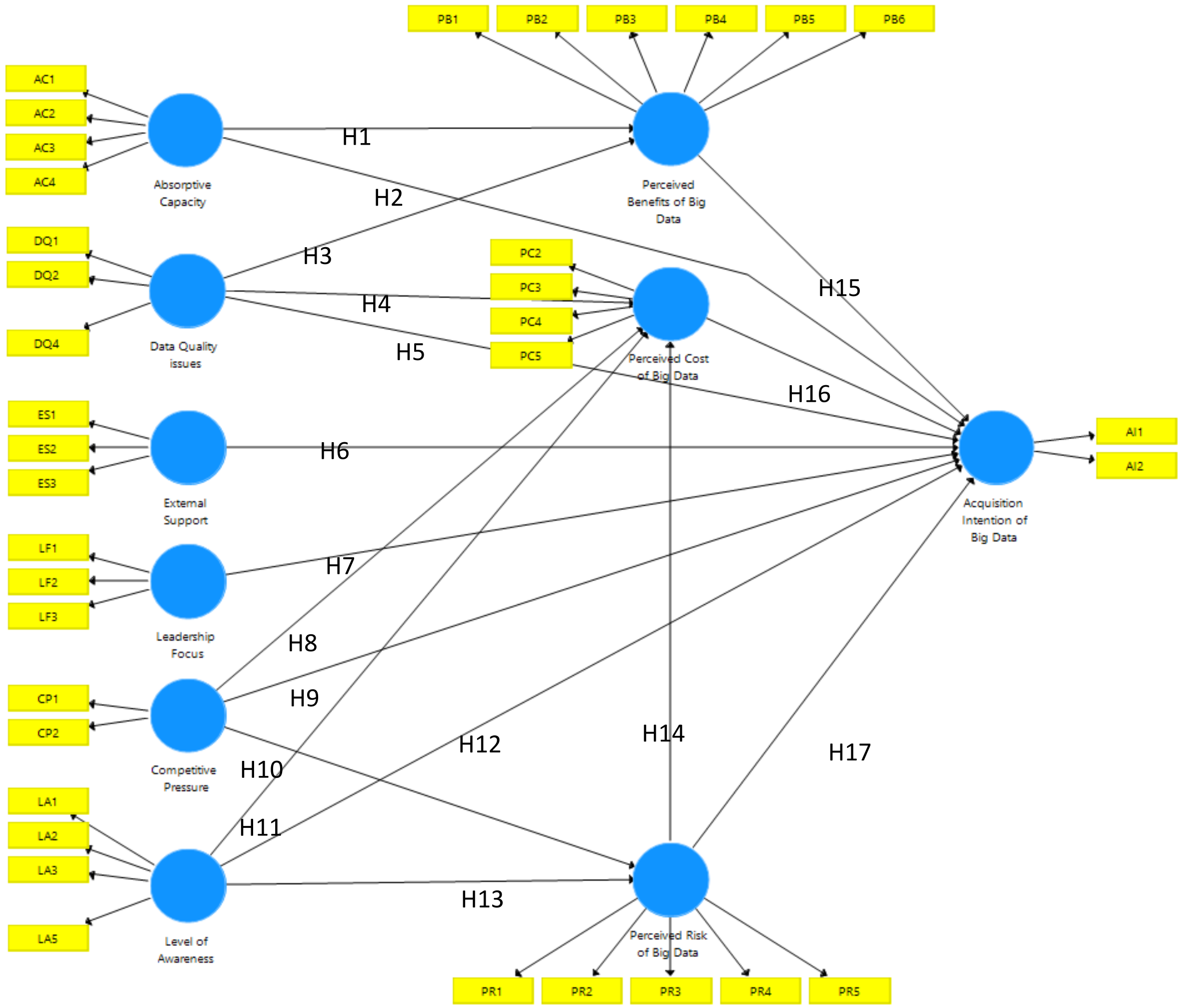


Figure 10: Proposed research model

3.5 Design of the research

3.5.1 Measurements

The research was started by obtaining the secondary data through the literature survey. Literature review was then conducted by using the key literatures, resulting in nine core factors. Subsequently, a survey was designed to collect the primary data for the research.

Measurement instrument was developed based on the literature review using a number of valid constructs and interviews with experts. The nine core constructs were predominantly identified from previous researchers and adequately adapted for the study. The construct, level of awareness and understanding was adapted from Izhar & Shoid (2016), Sivarajah et al. (2017), Tennakoon & Lasanthika (2020). The item, organizational absorptive capacity was adapted from Verma (2017), Shamim et al. (2018), Jha et al. (2020), Sancho-Zamora et al. (2021). The construct, organizational data quality issues was mainly inspired by Kwon et al. (2014), Bilal et al. (2016), Brohi et al. (2016), Verma (2017), Sivarajah et al. (2017), Côrte-Real et al. (2019). The construct, perceived benefits of Big Data was adapted from Esteves & Diaz (2013), Verma (2017). The construct, perceived cost of Big Data was adapted from Esteves & Diaz (2013), Bilal et al. (2016) Verma (2017), Sivarajah et al. (2017), Maroufkhani et al. (2020). The construct, perceived risk of Big Data was adapted from Bilal et al. (2016), Brohi et al. (2016) Sivarajah et al. (2017) Cabrera-Sánchez & Villarejo-Ramos (2019) Ajah & Nweke (2019) Maroufkhani et al. (2020). The construct, leadership focus was adapted from Shamim et al. (2018), Maroufkhani et al. (2020). The construct, external support was adapted from Cabrera-Sánchez & Villarejo-Ramos (2019), Maroufkhani et al. (2020). The construct, competitive pressure was inspired by Maroufkhani et al. (2020).

Noteworthy that the indicators of the constructs were only used as the foundation to develop the research constructs, that were not straightaway acquire from previous literature. This research uses a structured questionnaire to collect data from the potential respondents from the Sri Lankan construction industry. This research followed a quantitative approach.

3.5.2 Questionnaire development

The questionnaire was developed using LimeSurvey platform and was delivered to the respondents as an online survey. Respondents table was created using the LimeSurvey platform and the names and email addresses of the potential respondents. A unique survey link was automatically sent to the respondents through the platform.

Following the justifications of previous studies (Kwon et al., 2014; Verma, 2017; Shamim et al., 2018; Côrte-Real et al., 2019; Cabrera-Sánchez & Villarejo-Ramos, 2019; Maroufkhani et al., 2020; Shabbir & Gardezi, 2020), this research utilized a seven-point Likert scale with anchors ranging from ‘strongly disagree’ (1) to ‘strongly agree’ (7) except for initial questions of level of awareness and understanding. Whereas those constructs were measured utilizing a five-point Likert scale with anchors ranging from ‘not aware at all’ (1) to ‘extremely aware’ (5).

Questionnaire (see Annexure I) was developed under three main sections namely (1) General Information, (2) Factors and (3) Acquisition Intention. Table 3 shows the content and the question distribution among the identified factors.

Table 3: Content of the questionnaire

Item		Number of Questions	
		Main questions	Sub questions
1.0	**Section 01- General Information**	7	-
2.0	**Section 02 – Factors**		
2.1	Factor 1 – Level of awareness and understanding	2	7
2.2	Factor 2 – Absorptive capacity	1	5
2.3	Factor 3 – Data Quality	1	7
2.4	Factor 4 – Perceived Benefits	1	6
2.5	Factor 5 – Perceived Cost	1	5
2.6	Factor 6 – Perceived Risk	1	4
2.7	Factor 7 - Leadership Focus	1	3
2.8	Factor 8 –External Support from vendors	1	2
2.9	Factor 9 – Competitive Pressure	1	3
3.0	**Section 03 – Acquisition Intention**	1	2

The preliminary form of the questionnaire was pre-tested by two IT experts with mainly focusing on the key concept of the research: Big Data. Questionnaire was revised based on their inputs and then used for the pilot survey. The questionnaire was piloted with 18 potential respondents, identified from the construction sector and their feedback was reported. Necessary modifications were applied to the final survey based on the feedback provided on readability, coherence, understandability, and simplicity of completing the survey. The modified form of the questionnaire was then reviewed by two IT experts and two statistical experts for validation. Figure 11 illustrates the methodology of this research.

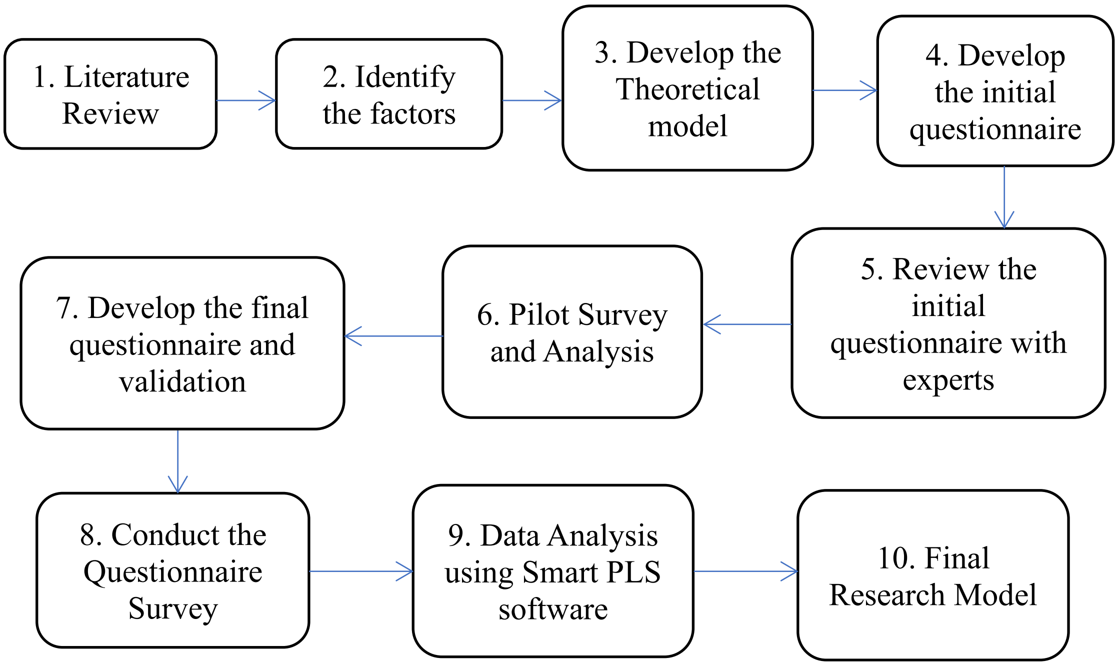


Figure 11: Research methodology

3.6 Sampling and Data Collection

Organizations in the construction sector that had adopted modern technologies and software for data management form the population of this research. The owner/managers of different areas are the main targeted respondents in this study. Executives and higher levels of management were targeted as the potential respondents, as they are assumed to be the main decision makers for innovation adoption and acquisition and have sufficient experience and information to answer the final questionnaire (Cabrera-Sánchez & Villarejo-Ramos, 2019; Maroufkhani et al., 2020).

The names and the email addresses of the potential respondents were collected and entered to the LimeSurvey platform by creating a participants table. A unique link of the online questionnaire survey was sent to the participants by email. Survey included a cover letter explaining the purpose of the research. The respondents were instructed to respond considering their most recent experience with technologies and innovation.

Most importantly, it assured the potential participant that participation in this research is completely voluntary.

3.7 Summary

Secondary data of this research was collected by thorough literature review and primary data was collected using a structured questionnaire. Questionnaire was developed using LimeSurvey platform and was delivered as an online survey. Executive and higher management levels were considered as potential respondents of this research.

CHAPTER 04: DATA ANALYSIS

4.1 Introduction

This chapter identifies the data collection and analysis of this research. It presents the analysis of the results that conducted using statistical techniques. This chapter follows the broadly accepted analysis reporting method of PLS analysis. Initially it assesses the measurement model considering indicator reliability, construct reliability, convergent validity, and discriminant validity. Further, it assesses the measurement model considering predictive capability, predictive relevance, path analysis and hypotheses testing. And then it concludes analyzing the mediating variables and the impact on the relationships.

4.2 Data Collection

In previous studies, respondents have limited to the people who have experience with BD technologies. Also, some researchers have identified the respondents from the organizations which already use BD technologies. As Sri Lankan construction industry is still at the early stage in digitalization, this research considered respondents with experience in modern technologies. And also, respondents are limiting by the level of knowledge they poses on modern technologies. Executives and above level of management were identified as the potential respondents.

A total of 371 survey invitations were sent to potential respondents. A total of 160 responses were returned. Out of 160 responses, 69 were incomplete responses, leaving 91 complete responses resulting in a response rate of 24.5%. The research also evaluated the reliability and validity of constructs by checking construct validity and discriminant validity (Maroufkhani et al., 2020).

4.3 Data analysis technique

The data was analyzed using quantitative data analysis technique. The proposed hypotheses were analyzed using the (PLS-SEM) partial least squares method of applying structural equation modeling (Shamim et al., 2018; Côrte-Real et al., 2019;

Maroufkhani et al., 2020). The latest version of Smart PLS software; Smart PLS 3.3.5, was used to test the research hypotheses of the proposed model. Further it was used to check the construct validity, factor analysis and path analysis.

Smart PLS software was mainly used because it is ideally suited when developing theories. Also, it does not require strict or precise sample distribution assumptions (Côrte-Real et al., 2019). Smart PLS software has especially been identified as suitable for studies using self-developed items (Shamim et al., 2018). This software analyses both structural model and the measurement model at once and it is effective in solving issues in constructs and indicators (Shamim et al., 2018). Table 4 shows a summary of data analysis techniques used by previous researchers.

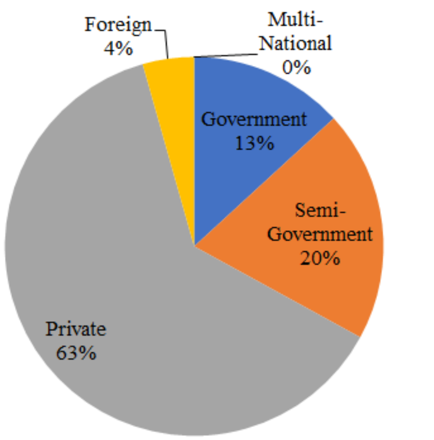
Table 4: Summary of Data analysis techniques

Focus area	Reference	Data Collection	Data Analysis
BDA adoption	(Maroufkhani et al., 2020)	Questionnaire Survey of 171 SMEs respondents in Manufacturing sector	Partial least squares (PLS), Structural model analysis
BDA capabilities and IOT capabilities	(Côrte-Realet al., 2019)	Questionnaire Survey of 618 respo. SAP customers	Partial least squares (PLS) with SmartPLS 3.0
BDA capability	Jha et al., 2020	Semi-structured open-ended interviews	Snowball method
BD decision making capability	Shamim et al., 2018	86 structured questionnaires in Chinese firms	PLS method of applying structural equation modeling (SEM), SmartPLS software
Intention to adopt BD services	Verma, 2017	Questionnaire Survey with 205 responses	Partial Least Square (PLS) technique, SmartPLS 2.0 M3 software
Acquisition intension of BDA	Kwon et al., 2014	Survey with 306 responses	Structural equation modeling based on partial least squares analysis using SmartPLS 2.0
Adoption of BDA	Cabrera-Sánchez & Villarejo-Ramos A. F., 2019	199 responses of CEOs and managers	Partial least squares with statistical software Smart PLS 3.2.3

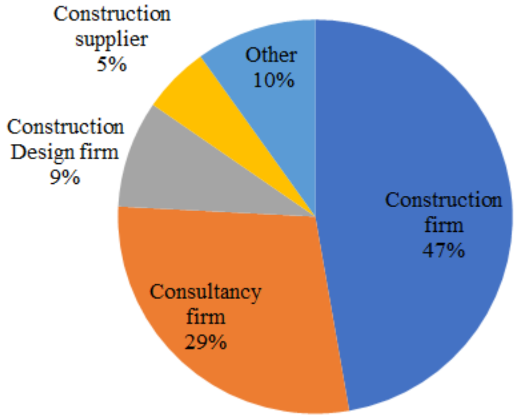
The analysis of the research was followed widely accepted reporting method of PLS SEM analysis as suggested by previous literature (Chin, 2010; Maroufkhani et al., 2020; Shamim et al., 2018)

4.4 General Information

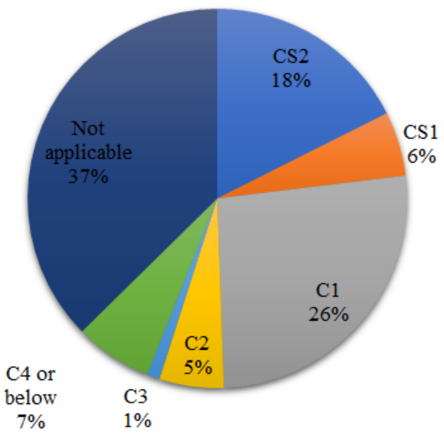
The majority of respondents (see Figure 12) were from private sector organizations (57, 62.64%) while other were from semi government (18, 19.78%), government (12, 13.19%) and foreign (4, 4.40%). Most of the respondents were from construction firms (43, 47.25%) while 26 (28.57%) respondents were from consultancy firms. There were 8 (8.79%) respondents from construction design firms, 5 (5.49%) from construction service/ material supplier firms and 9 (9.89%) from other category.



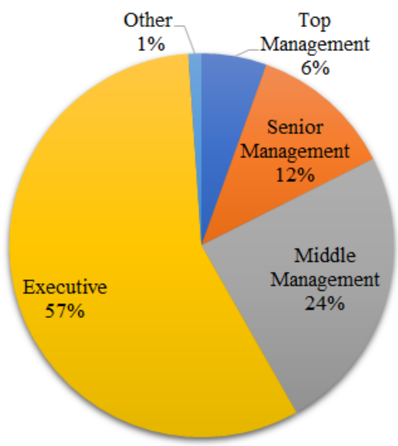
a: Organization Sector



b: Organization Type



c: Organization Grade



d: Designation

Figure 12: Preliminary information of respondents. (a): Organization sector. (b): Organization type. (c): Organization grade. (d): Designation

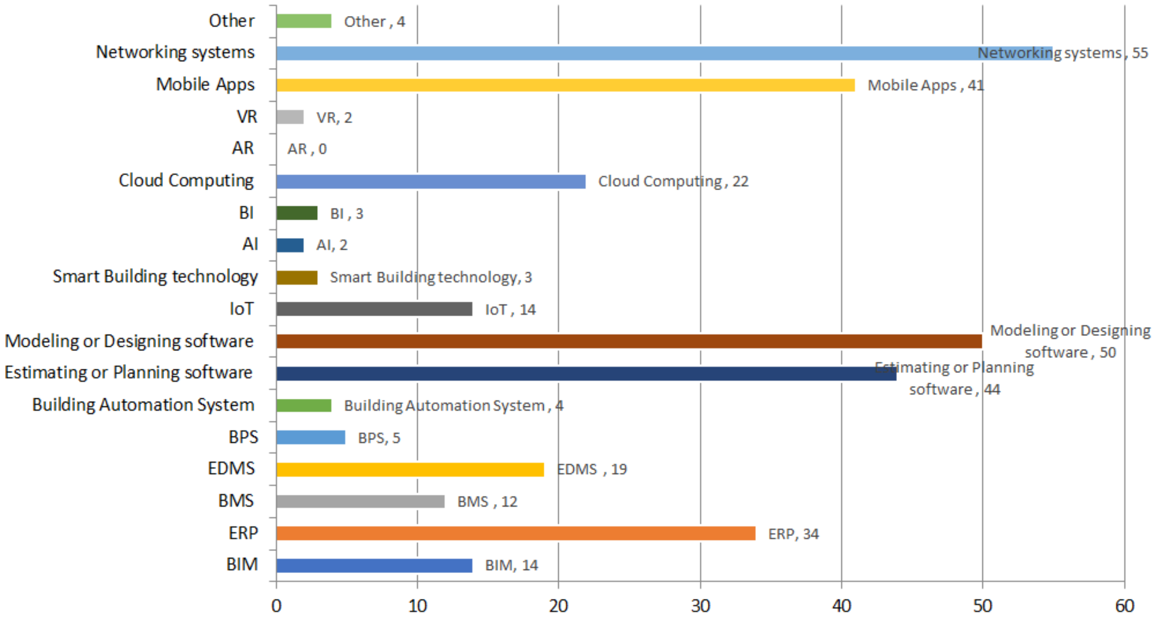
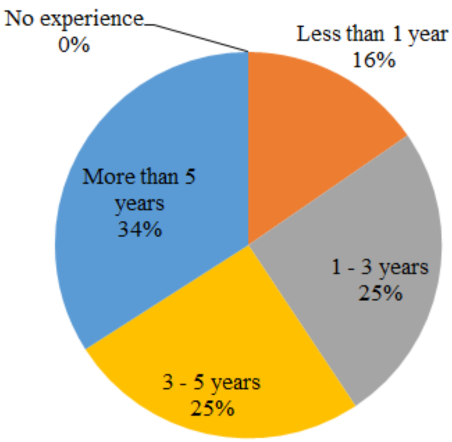
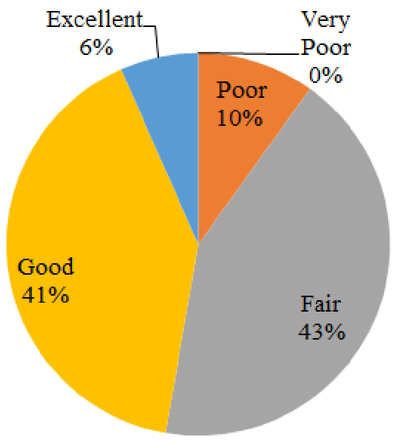


Figure 13: Number of technologies use in the respondents' organization

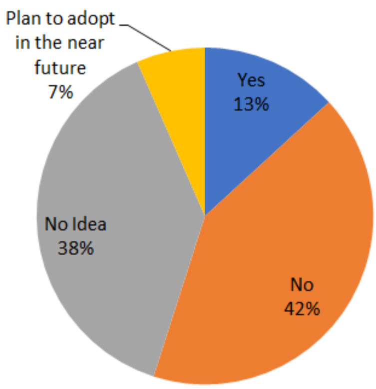


a: Years of experience with modern technologies

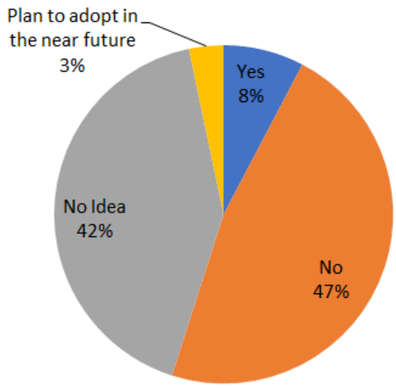


b: Level of knowledge on modern technologies

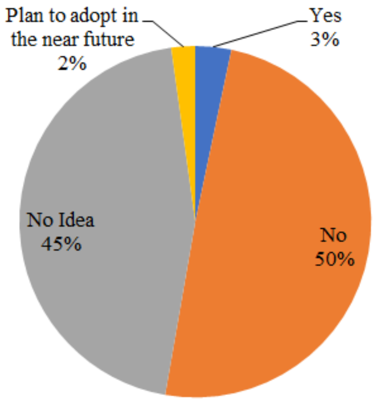
Figure 14: Association with modern technologies. (a): Years of experience with modern technologies. (b): Level of knowledge on modern technologies



a: Number of respondents mentioned the use of BD Storage system



b: Number of respondents mentioned the use of BD Processing tools



c: Number of respondents mentioned the use of BDA

Figure 15: Number of respondents mentions the use of BD in their organizations. (a): Use of BD Storage system. (b): Use of BD Processing tools. (c): Use of BDA

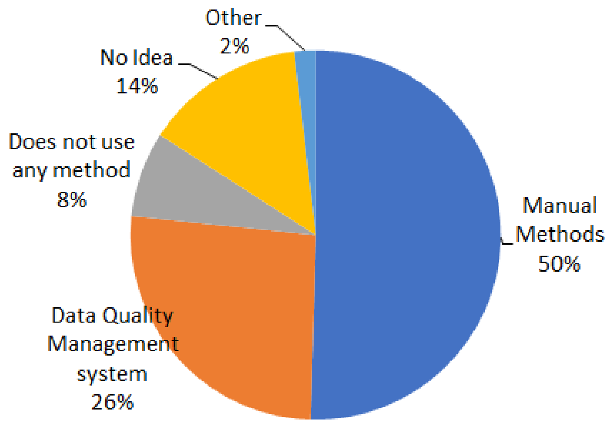
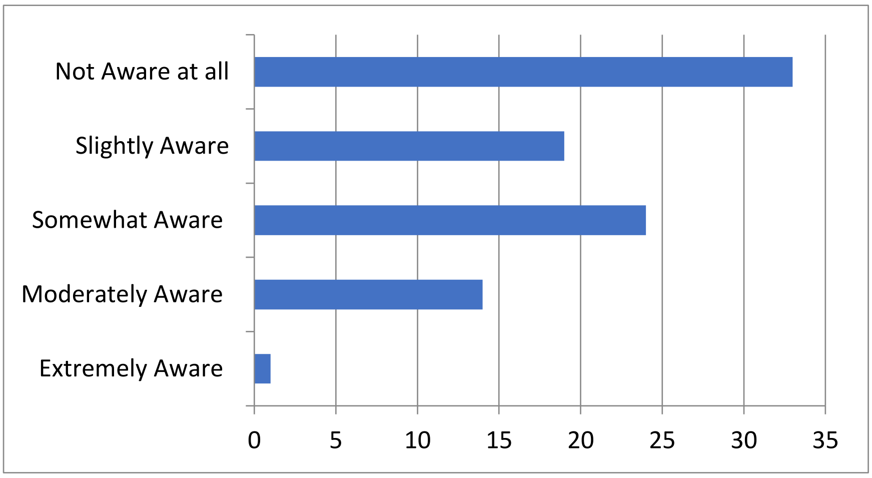


Figure 16: Usage of Data quality assessment model

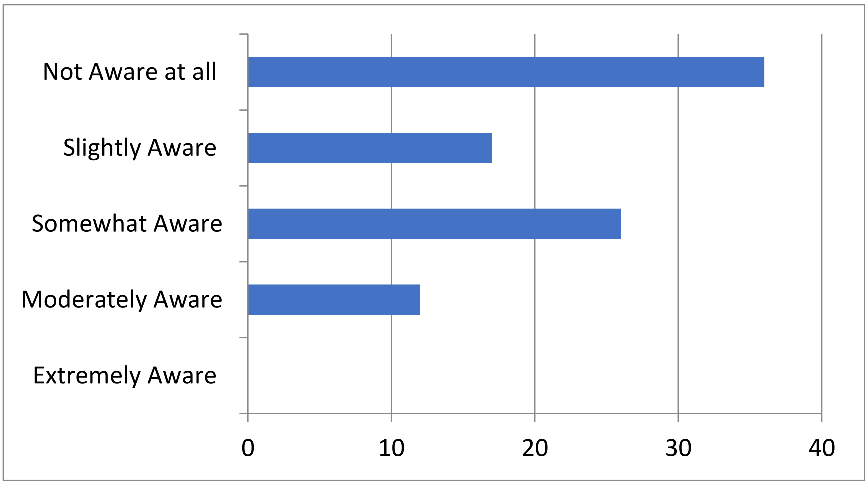
According to Figure 16, most of the organizations use manual method (50%) to assess, control and improve the organizational data.

4.4.1 Level of Awareness and understanding on Big Data

Initially it was assessed the awareness level of the respondents on BD technologies (See Figure 17). Majority of the respondents were not aware at all on the term BD (36.26%) and BDA (39.56%).



a: Number of respondents aware on term BD



b: Number of respondents aware on term BDA

Figure 17: Number of respondents aware on BD terms. a: Number of respondents aware on term BD. b: Number of respondents aware on term BDA

4.5 Assessment of Measurement model

The measurement model was assessed based on indicator reliability, construct reliability and construct validities (convergent validity and discriminant validity). Factor loadings, Cronbach's Alpha, composite reliability (CR) and average variance extract (AVE) were initially examined to assess the convergence of the constructs.

4.5.1 Convergent Validity

As suggested by Kwon et al. (2014), Shamim et al. (2018) and Maroufkhani et al. (2020), the threshold values of factor loadings, Cronbach's alpha, CR and AVE should be higher than 0.7, 0.7, 0.7 and 0.5, respectively. According to Henseler (2009) (see Table 5) if indicator reliability of an item is less 0.7 (see Table 5), that item can be deleted only if it is significantly improving the CR and AVE (see the Table 6).

Table 5: Assessing Reflective measurement model (Henseler, 2009)

Criterion	Description
Composite reliability (ρ_c)	$\rho_c = (\sum \lambda_i)^2/[(\sum \lambda_i)^2 + \sum Var(\varepsilon_i)]$, where λ_i is the outer (component) loading to an indicator, and $Var(\varepsilon_i) = 1 - \lambda_i^2$ in case of standardized indicators. The composite reliability is a measure of internal consistency and must not be lower than 0.6.
Indicator reliability	Absolute standardized outer (component) loadings should be higher than 0.7.
Average variance extracted (AVE)	$\text{AVE} = (\sum \lambda_i^2)/[\sum \lambda_i^2 + \sum Var(\varepsilon_i)]$, where λ_i is the component loading to an indicator and $Var(\varepsilon_i) = 1 - \lambda_i^2$ in case of standardized indicators. The average variance extracted should be higher than 0.5.
Fornell–Larcker criterion	In order to ensure discriminant validity, the AVE of each latent variable should be higher than the squared correlations with all other latent variables. Thereby, each latent variable shares more variance with its own block of indicators than with another latent variable representing a different block of indicators.
Cross-loadings	Cross-loadings offer another check for discriminant validity. If an indicator has a higher correlation with another latent variable than with its respective latent variable, the appropriateness of the model should be reconsidered.

Thus, three items (DQ3, LA4 and LA6) were removed considering the initial values of factor loadings. Table 6 represents the factor loadings and the cross loadings for the measurement model with good indicator reliability.

Table 6: Factor loadings and cross loadings for the measurement model

	AC	AQ	CP	DQ	ES	LA	LF	PB	PC	PR
AC1	**0.823**	0.38	0.358	-0.397	0.402	0.312	0.468	-0.517	0.394	0.368
AC2	**0.876**	0.503	0.449	-0.475	0.402	0.325	0.577	-0.616	0.473	0.37
AC3	**0.883**	0.403	0.316	-0.501	0.465	0.375	0.589	-0.624	0.553	0.38
AC4	**0.801**	0.433	0.405	-0.386	0.436	0.347	0.481	-0.537	0.532	0.326
AQ1	0.29	**0.825**	0.228	-0.184	0.278	0.437	0.259	-0.239	0.302	0.41
AQ2	0.56	**0.933**	0.537	-0.502	0.486	0.365	0.618	-0.568	0.463	0.377
CP1	0.427	0.479	**0.973**	-0.418	0.513	0.201	0.515	-0.507	0.609	0.513
CP2	0.453	0.427	**0.969**	-0.426	0.521	0.135	0.473	-0.546	0.585	0.502
DQ1	-0.488	-0.392	-0.398	**0.887**	-0.505	-0.069	-0.568	0.719	-0.368	-0.159
DQ2	-0.383	-0.41	-0.397	**0.841**	-0.478	-0.118	-0.517	0.552	-0.313	-0.199
DQ4	-0.394	-0.221	-0.253	**0.700**	-0.369	-0.28	-0.3	0.581	-0.346	-0.408
ES1	0.349	0.455	0.567	-0.472	**0.831**	0.175	0.53	-0.469	0.489	0.436
ES2	0.533	0.412	0.416	-0.538	**0.921**	0.217	0.539	-0.547	0.47	0.374
ES3	0.448	0.28	0.37	-0.44	**0.871**	0.187	0.421	-0.466	0.402	0.354
LA1	0.32	0.338	0.048	-0.08	0.108	**0.847**	0.207	-0.164	0.035	0.263
LA2	0.325	0.326	0.057	-0.083	0.114	**0.835**	0.211	-0.146	0.05	0.221
LA3	0.31	0.445	0.248	-0.183	0.217	**0.847**	0.268	-0.264	0.26	0.386
LA5	0.309	0.224	0.145	-0.21	0.242	**0.574**	0.157	-0.237	0.273	0.33
LF1	0.585	0.514	0.503	-0.555	0.575	0.236	**0.966**	-0.608	0.48	0.391
LF2	0.634	0.521	0.517	-0.567	0.569	0.281	**0.980**	-0.643	0.469	0.363
LF3	0.616	0.534	0.469	-0.566	0.552	0.289	**0.975**	-0.627	0.44	0.351
PB1	-0.51	-0.425	-0.325	0.587	-0.517	-0.192	-0.511	**0.768**	-0.311	-0.262

	AC	AQ	CP	DQ	ES	LA	LF	PB	PC	PR
PB2	-0.569	-0.422	-0.551	0.629	-0.533	-0.217	-0.526	**0.867**	-0.5	-0.47
PB3	-0.638	-0.44	-0.487	0.673	-0.474	-0.272	-0.518	**0.895**	-0.47	-0.366
PB4	-0.591	-0.384	-0.531	0.655	-0.42	-0.232	-0.539	**0.881**	-0.516	-0.479
PB5	-0.602	-0.383	-0.372	0.663	-0.484	-0.232	-0.584	**0.853**	-0.495	-0.365
PB6	-0.597	-0.49	-0.518	0.731	-0.509	-0.223	-0.636	**0.891**	-0.523	-0.38
PC2	0.551	0.368	0.511	-0.333	0.473	0.183	0.42	-0.487	**0.940**	0.631
PC3	0.586	0.416	0.578	-0.431	0.515	0.152	0.451	-0.529	**0.938**	0.619
PC4	0.519	0.442	0.664	-0.4	0.449	0.255	0.46	-0.53	**0.921**	0.684
PC5	0.504	0.445	0.532	-0.405	0.534	0.183	0.441	-0.495	**0.934**	0.611
PR1	0.307	0.329	0.343	-0.232	0.267	0.398	0.279	-0.32	0.545	**0.837**
PR2	0.369	0.367	0.486	-0.308	0.419	0.336	0.35	-0.405	0.659	**0.889**
PR3	0.33	0.381	0.435	-0.2	0.374	0.292	0.312	-0.397	0.498	**0.760**
PR4	0.377	0.388	0.537	-0.272	0.41	0.301	0.306	-0.368	0.636	**0.870**
PR5	0.395	0.355	0.348	-0.232	0.4	0.315	0.328	-0.386	0.479	**0.799**

Note: AC - Absorptive Capacity, AQ - Acquisition Intention, CP - Competitive Pressure, DQ - Data Quality, ES - External Support, LA - Level of Awareness, LF - Leadership Focus, PB - Perceived Benefits, PC - Perceived Cost, PR - Perceived Risk

Table 7 represents the results of Cronbach's alpha, composite reliability, and AVE. All the constructs present Cronbach's alpha above 0.70, composite reliability above 0.70 and AVE above 0.5. As all the constructs meets the threshold value, it can demonstrate the convergent validity is acceptable.

Table 7: Results of Cronbach's alpha, composite reliability, and AVE

	Cronbach's Alpha	rho_A	CR	AVE
Absorptive Capacity	0.868	0.874	0.910	0.716
Acquisition Intension of Big Data	0.724	0.879	0.871	0.773
Competitive Pressure	0.940	0.942	0.971	0.943
Data Quality issues	0.738	0.759	0.853	0.661
External Support	0.850	0.875	0.908	0.766
Leadership Focus	0.972	0.973	0.982	0.948
Level of Awareness	0.783	0.814	0.860	0.609
Perceived Cost of Big Data	0.951	0.954	0.964	0.871
Perceived Risk of Big Data	0.888	0.896	0.918	0.693
Perceived benefits of Big Data	0.929	0.932	0.945	0.740

Considering the above results, it can conclude that construct validity of the measurement model is in the satisfactory level.

4.5.2 Discriminant Validity

Discriminant validity was evaluated to indicate the extent to which the variables in the model discriminate from other variables in the same model (Farrell, 2010). Concerning the PLS context, a construct needs to share more variance with it measures more than it shares with other constructs in the same model (Verma, 2017). Assessment of discriminant validity is important in the research in order to prevent the multi collinearity issues of latent variables (Hamid et al., 2017).

Discriminant validity was evaluated using Fornell & Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio of correlations method (Maroufkhani et al., 2020). In Fornell & Larcker criterion, the square root of AVE of each construct should be greater than the inter-construct correlation (Kwon et al., 2014; Verma, 2017; Côrte-Real et al., 2019). Table 8 represents the results of Fornell & Larcker criterion where AVE of each construct is given in bold. As shown in Table 7, inter construct correlations are less than the square root of AVE values, thus confirming discriminant validity.

Table 8: Discriminant Validity (Fornell & Larcker criterion)

	AC	AQ	CP	DQ	ES	LF	LA	PB	PC	PR
AC	**0.846**									
AQ	0.516	**0.879**								
CP	0.453	0.474	**0.971**							
DQ	-0.522	-0.431	-0.434	**0.813**						
ES	0.503	0.458	0.532	-0.558	**0.875**					
LF	0.628	0.545	0.509	-0.578	0.58	**0.974**				
LA	0.401	0.44	0.179	-0.184	0.225	0.278	**0.782**			
PB	-0.68	-0.501	-0.542	0.765	-0.568	-0.643	-0.269	**0.86**		
PC	0.578	0.452	0.617	-0.422	0.527	0.476	0.216	-0.548	**0.933**	
PR	0.427	0.436	0.525	-0.302	0.452	0.378	0.395	-0.451	0.685	**0.832**

Note: AC - Absorptive Capacity, AQ - Acquisition Intention, CP - Competitive Pressure, DQ - Data Quality, ES - External Support, LA - Level of Awareness, LF - Leadership Focus, PB - Perceived Benefits, PC - Perceived Cost, PR - Perceived Risk

Further, discriminant validity was examined using the cross loadings table (Côrte-Real et al., 2019). According to the results obtained, the factor loadings of each indicator is higher than all cross loadings of other constructs including the threshold value of factor loadings is greater than 0.70. This criterion satisfies for this research, according to the cross-loading table obtained after calculations (Hamid et al., 2017).

Moreover, Heterotrait-Monotrait (HTMT) criteria (Maroufkhani et al., 2020) which is one of the most important and latest criteria of evaluating the discriminant validity was examined. The threshold value of HTMT criteria was considered as values below 0.9 (Côrte-Real et al., 2019). Table 9 represents the values of HTMT criteria which indicate good discriminant validity.

Table 9: Discriminant Validity (Heterotrait-Monotrait (HTMT) ratio)

	AC	AQ	CP	DQ	ES	LF	LA	PB	PC	PR
AC										
AQ	0.602									
CP	0.501	0.522								
DQ	0.647	0.526	0.518							
ES	0.589	0.526	0.575	0.693						
LF	0.680	0.590	0.532	0.673	0.623					
LA	0.493	0.585	0.185	0.249	0.268	0.310				
PB	0.755	0.555	0.578	0.899	0.635	0.676	0.305			
PC	0.636	0.519	0.647	0.503	0.575	0.494	0.235	0.580		
PR	0.487	0.555	0.565	0.386	0.508	0.408	0.464	0.497	0.736	

Note: AC - Absorptive Capacity, AQ - Acquisition Intention, CP - Competitive Pressure, DQ - Data Quality, ES - External Support, LA - Level of Awareness, LF - Leadership Focus, PB - Perceived Benefits, PC - Perceived Cost, PR - Perceived Risk

With that it can conclude that all the constructs mentioned above, present a satisfactory level of discrimination for the measurement model.

Therefore, it can be concluded that the structural model has a satisfactory indicator reliability, construct reliability, convergent validity, and discriminant validity. Consequently, the constructs can, therefore, be considered to test the structural model.

4.5.3 Updated research model

Following from reliability and validity analyses, initial proposed research model was updated consequently. The updated research model illustrates all the latent variables and their acceptable indicators.

Perceived benefits of Big Data, perceived cost of Big Data and perceived risk of Big Data were used as the moderating variables in the research model. Moderating effects of these variables were evaluated using SmartPLS software. Figure 18 represents the updated research model.

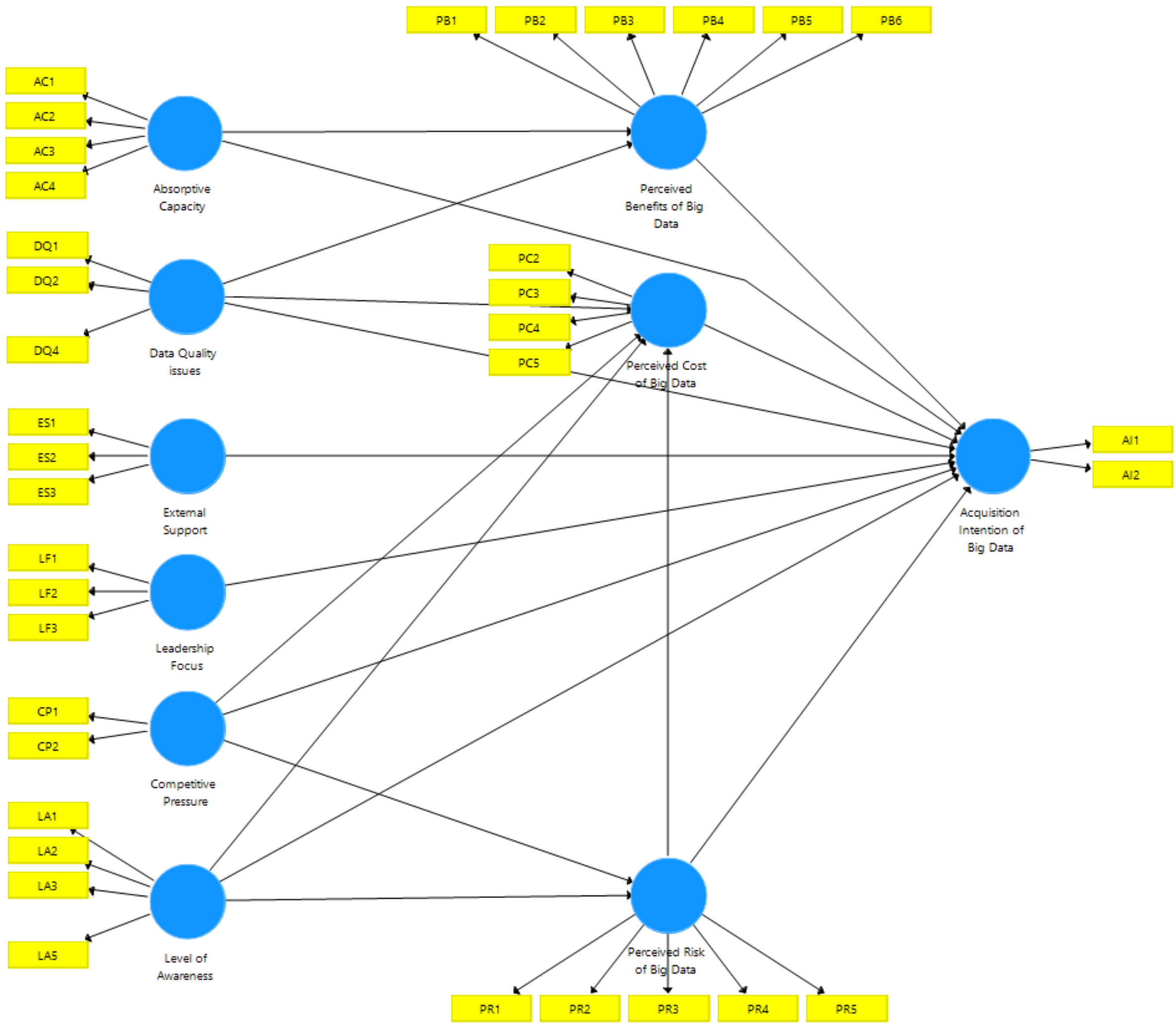


Figure 18: Updated research model

4.6 Assessment of structural model

After analyzing the measurement model, the hypotheses were tested by examining the structural model using SmartPLS 3.3.5 software. The structural model was examined using the coefficient of determination; R-squared (R^2) value (variance explained by the independent variables), and path coefficients (Kwon et al., 2014; Verma, 2017; Côrte-Real et al., 2019; Maroufkhani et al., 2020; Sarstedt et al., 2021).

4.6.1 Coefficient of determination (R-Squared) – Predictive capability

R- Squared, the coefficient of determination is a regression statistical measure of how close the data are to the fitted regression line (Sarstedt et al., 2021). The value of R - squared explains the percentage of the dependent variables' movement by a tested independent variable (Hair et al., 2011). Whereas 0% of R- squared indicates that the model does not explain the variability of the response data around its means (Hair et al., 2011). While the value got close to 100% means that the model explains all the variability of the response data around its mean. In general, a higher R - squared value indicates higher level of accuracy (Hair et al., 2011) with better the model fits the data (Côrte-Real et al., 2019).

Table 10 represents the values of R^2 which were obtained using SmartPLS software. Evaluation outlines that 58.0% of perceived cost of Big Data variation is explained by the proposed research model. Additionally, 69.4% and 37.0% of variations are explained for perceived benefits of Big Data and perceived risk of Big Data respectively. Finally, 45.4% of Acquisition intention of Big Data variation is explained by the research model.

Table 10: Values of coefficient of determination (R- squared)

	R Square	R Square Adjusted
Acquisition Intension of Big Data	0.454	0.393
Perceived Cost of Big Data	0.580	0.561
Perceived Risk of Big Data	0.370	0.356
Perceived benefits of Big Data	0.694	0.687

The results in the Table 10 shows that the values of R- squared are over 0.1. Hence it can conclude that the predictive capability of the model is established.

4.6.2 Path analysis and hypotheses testing

In SmartPLS, bootstrapping allows evaluating and testing the statistical significance of PLS-SEM results (Côrte-Real et al., 2019). This research applied nonparametric bootstrapping procedure with 5,000 resamples (Shamim et al., 2018; Côrte-Real et al., 2019; Maroufkhani et al., 2020). The complete bootstrapping process with 5,000 subsamples with a 5% significance level ($p < 0.05$) was used (Verma, 2017). The structural model was assessed by examining the path coefficients (Verma, 2017; Shamim et al., 2018; Cabrera-Sánchez & Villarejo-Ramos, 2019; Maroufkhani et al., 2020) and t - value (Verma, 2017; Côrte-Real et al., 2019).

In previous studies, it was clarified in reporting p values as $p \leq 0.05$, $p \leq 0.01$ or $p \leq 0.001$ and confirmed it is sufficient and constructive (Gopakumar et al., 2015; Wasserstein et al., 2019; Leo & Sardanelli, 2020). With a 5% significance level, the path coefficient is considered significant when the t statistic value is greater than 1.96. When the significance level is 0.1, the path coefficient is considered significant for t statistics greater than 1.65 (Wong, 2013; Verma, 2017).

After the assessment of predictive capability and predictive relevance of the research, hypotheses were tested to make sure the significance of the relationships. Table 11 summarizes the hypothesis results of the research. The following discussion shows the assessment of the hypotheses generated from the research.

1. H1 evaluates whether Organizational absorptive capacity (AC) has a significant impact on the Perceived benefits of Big Data (PB). The results revealed that AC has an insignificant impact on PB (β = -0.386, t = 5.640, $p<0.001$). Hence H1 was not supported.

2. H2 evaluates whether Organizational absorptive capacity (AC) has a significant impact on the Acquisition intention of Big Data (AQ). The results revealed that AC has an insignificant impact on AQ (β = 0.078, t = 0.624, p>0.05). Hence H2 was not supported.

3. H3 evaluates whether Organizational data quality issues (DQ) has a significant impact on the Perceived benefits of Big Data (PB). The results revealed that DQ has a significant impact on PB (β = 0.563, t = 8.806, p<0.001). Hence H3 was supported.

4. H4 evaluates whether Organizational data quality issues (DQ) has a significant impact on the Perceived cost of Big Data (PC). The results revealed that DQ has an insignificant impact on PC (β = -0.152, t = 1.692, p<0.01). Hence H4 was not supported.

5. H5 evaluates whether Organizational data quality issues (DQ) has a significant impact on the Acquisition intention of Big Data (AQ). The results revealed that DQ has an insignificant impact on AQ (β = -0.064, t = 0.529, p> 0.05). Hence H5 was not supported.

6. H6 evaluates whether External support (ES) has a significant impact on the Acquisition intention of Big Data (AQ). The results revealed that ES has an insignificant impact on AQ (β = 0.052, t = 0.428, p > 0.05). Hence H6 was not supported.

7. H7 evaluates whether Leadership Focus (LF) has a significant impact on the Acquisition intention of Big Data (AQ). The results revealed that LF has an insignificant impact on AQ (β = 0.221, t = 1.532, p > 0.05). Hence H7 was not supported.

8. H8 evaluates whether Competitive pressure (CP) has a significant impact on the Perceived cost of Big Data (PC). The results revealed that CP has an insignificant impact on PC (β = 0.296, t = 2.823, p <0.01). Hence H8 was supported.

9. H9 evaluates whether Competitive pressure (CP) has a significant impact on the Acquisition intention of Big Data (AQ). The results revealed that CP has an insignificant impact on AQ (β = 0.150, t = 1.515, p > 0.05). Hence H9 was not supported.

10. H10 evaluates whether Competitive pressure (CP) has a significant impact on the Perceived risk of Big Data (PR). The results revealed that CP has a significant impact on PR (β = 0.469, t = 4.646, p < 0.001). Hence H10 was supported.

11. H11 evaluates whether Level of awareness and understanding (LA) has a significant impact on the Perceived cost of Big Data (PC). The results revealed that LA has a significant impact on PC (β = 0.065, t = 0.719, p>0.05). Hence H11 was not supported.

12. H12 evaluates whether Level of awareness and understanding (LA) has a significant impact on the Acquisition intention of Big Data (AQ). The results revealed that LA has a significant impact on AQ (β = 0.265, t = 1.981, p<0.05). Hence H12 was supported.

13. H13 evaluates whether Level of awareness and understanding (LA) has a significant impact on the Perceived risk of Big Data (PR). The results revealed that LA has a significant impact on PR (β = 0.311, t = 2.969, p<0.01). Hence H13 was supported.

14. H14 evaluates whether Perceived risk of Big Data (PR) has a significant impact on the Perceived cost of Big Data (PC). The results revealed that PR has a significant impact on PC (β = 0.509, t = 5.110, p<0.001). Hence H14 was supported.

15. H15 evaluates whether Perceived benefits of Big Data (PB) has a significant impact on the Acquisition intention of Big Data (AQ). The results revealed that PB has an insignificant impact on AQ (β = -0.023, t = 0.168, p > 0.05). Hence H15 was not supported.

16. H16 evaluates whether Perceived cost of Big Data (PC) has a significant impact on the Acquisition intention of Big Data (AQ). The results revealed that PC has an insignificant impact on AQ (β = 0.054, t = 0.317, p > 0.05). Hence H16 was not supported.

17. H15 evaluates whether Perceived risk of Big Data (PR) has a significant impact on the Acquisition intention of Big Data (AQ). The results revealed that PR has an insignificant impact on AQ (β = 0.052, t = 0.314, p > 0.05). Hence H15 was not supported.

Table 11: Results of hypotheses testing

	Relationship	β	M	STDEV	T Statistics	P Values	Validation
H1	AC -> PB	-0.386	-0.389	0.069	5.640	0.000	Not Supported (Significant but negative effect is observed)
H2	AC -> AQ	0.078	0.102	0.125	0.624	0.533	Not Supported
H3	DQ -> PB	0.563	0.561	0.064	8.806	0.000	Supported
H4	DQ -> PC	-0.152	-0.155	0.090	1.692	0.091	Not Supported (Significant but negative effect is observed)
H5	DQ -> AQ	-0.064	-0.058	0.122	0.529	0.597	Not Supported
H6	ES -> AQ	0.052	0.072	0.122	0.428	0.668	Not Supported
H7	LF -> AQ	0.221	0.198	0.144	1.532	0.126	Not Supported
H8	CP -> PC	0.296	0.294	0.105	2.823	0.005	Supported
H9	CP -> AQ	0.150	0.151	0.105	1.515	0.130	Not Supported
H10	CP -> PR	0.469	0.464	0.079	6.041	0.000	Supported
H11	LA -> PC	-0.065	-0.058	0.09	0.719	0.472	Not Supported
H12	LA -> AQ	0.265	0.281	0.128	1.981	0.048	Supported
H13	LA -> PR	0.311	0.314	0.105	2.924	0.003	Supported
H14	PR -> PC	0.509	0.503	0.100	5.110	0.000	Supported
H15	PB -> AQ	-0.023	-0.014	0.146	0.168	0.866	Not Supported
H16	PC -> AQ	0.054	0.051	0.154	0.317	0.725	Not Supported
H17	PR -> AQ	0.052	0.049	0.152	0.314	0.753	Not Supported

Note: AC - Absorptive Capacity, AQ - Acquisition Intention, CP - Competitive Pressure, DQ - Data Quality, ES - External Support, LA - Level of Awareness, LF - Leadership Focus, PB - Perceived Benefits, PC - Perceived Cost, PR - Perceived Risk

4.6.3 Mediation analysis

Mediation can be identified when the effect of an independent variable (IV) is transmitted on a dependent variable (DV) through one or more other mediator variables.

Figure 19 and Figure 20 shows the impact on IV on DV without mediator and with mediator. Total effect is represented by c, while indirect effect and direct effects have represented by (a*b) and c’ respectively.

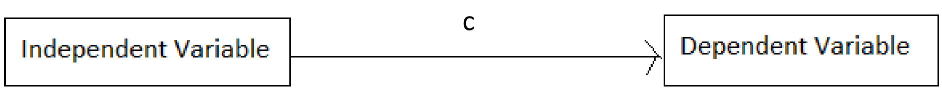


Figure 19: Impact on IV on DV without any mediator. Source: (Aguinis et al., 2017)

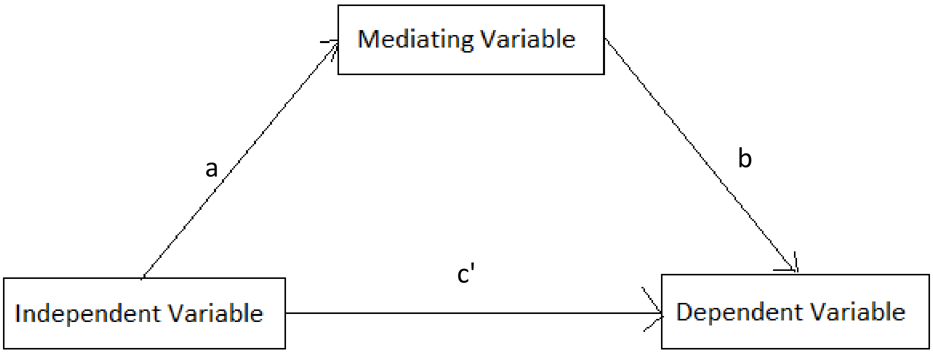


Figure 20: Impact on IV on DV with a mediator. Source: (Aguinis et al., 2017)

Mediation can be either complete or partial according to the effect. Complete mediation occurs when the total effect of an IV on a DV is transmitted through one or more mediator variables. Therefore, there is no direct effect on the DV, and the entire effect is indirect. Partial mediation occurs when an IV has both direct effect and indirect effect on a DV. (Aguinis et al., 2017) Therefore the path a*b (indirect effect) and the path c’ (direct effect) are significant. No mediation occurs when the indirect effect is insignificant.

This section identifies the three-mediation effect of perceived benefits of Big Data, perceived cost of big data and perceived risk of big data. Mediation analysis was performed with SmartPLS software and assessed the mediating roles of the identified variables. PLS-SEM results and bootstrapping procedure provide the direct effect (Table 11), specific indirect effect (Table 12), and the total effect (Table 13) outcomes (Hair et al. 2017). Table 12 and table 13 represent the specific indirect effect and the total effect of the relationships, respectively.

Table 12: Specific indirect effect

Relationship	β	Sample Mean (M)	STDEV	T Statistics	P Values	Validation
LA -> PR -> PC	0.161	0.161	0.065	2.462	0.014	Supported
CP -> PR -> AQ	0.022	0.013	0.070	0.308	0.758	Not Supported
CP -> PC -> AQ	0.014	0.015	0.05	0.292	0.771	Not Supported
LA -> PC -> AQ	-0.003	-0.007	0.017	0.182	0.855	Not Supported
LA -> PR -> AQ	0.015	0.011	0.051	0.289	0.773	Not Supported
CP -> PR -> PC	0.237	0.232	0.058	4.053	0.000	Supported
DQ -> PC -> AQ	-0.007	-0.007	0.029	0.253	0.800	Not Supported
PR -> PC -> AQ	0.025	0.023	0.079	0.316	0.752	Not Supported
AC -> PB -> AQ	0.009	0.007	0.057	0.165	0.869	Not Supported
LA -> PR -> PC -> AQ	0.008	0.005	0.026	0.307	0.759	Not Supported
DQ -> PB -> AQ	-0.014	-0.008	0.083	0.166	0.868	Not Supported
CP -> PR -> PC -> AQ	0.012	0.012	0.037	0.31	0.757	Not Supported

Note: AC - Absorptive Capacity, AQ - Acquisition Intention, CP - Competitive Pressure, DQ - Data Quality, ES - External Support, LA - Level of Awareness, LF - Leadership Focus, PB - Perceived Benefits, PC - Perceived Cost, PR - Perceived Risk

Table 13: Total effect

Relationship	β	Sample Mean (M)	STDEV	T Statistics	P Values	Validation
AC -> AQ	0.087	0.109	0.125	0.697	0.486	Not Supported
AC -> PB	-0.386	-0.389	0.068	5.684	0.000	Not Supported (Significant but negative effect is observed)
CP -> AQ	0.204	0.204	0.119	1.721	0.085	Not Supported
CP -> PC	0.287	0.287	0.063	4.565	0.000	Supported
CP -> PR	0.469	0.464	0.079	5.96	0.000	Supported
DQ -> AQ	-0.085	-0.074	0.102	0.840	0.401	Not Supported
DQ -> PC	-0.237	-0.243	0.088	2.685	0.007	Not Supported (Significant but negative effect is observed)
DQ -> PB	0.563	0.561	0.065	8.729	0.000	Supported
ES -> AQ	0.055	0.072	0.123	0.449	0.654	Not Supported
LF -> AQ	0.213	0.187	0.15	1.419	0.156	Not Supported
LA -> AQ	0.277	0.280	0.114	2.424	0.015	Supported
LA -> PC	0.19	0.193	0.066	2.877	0.004	Supported
LA -> PR	0.311	0.314	0.105	2.969	0.003	Supported
PC -> AQ	0.054	0.051	0.154	0.352	0.725	Not Supported
PR -> AQ	0.071	0.054	0.145	0.492	0.622	Not Supported
PR -> PC	0.612	0.615	0.067	9.149	0.000	Supported
PB -> AQ	-0.023	-0.014	0.146	0.158	0.874	Not Supported

Note: AC - Absorptive Capacity, AQ - Acquisition Intention, CP - Competitive Pressure, DQ - Data Quality, ES - External Support, LA - Level of Awareness, LF - Leadership Focus, PB - Perceived Benefits, PC - Perceived Cost, PR - Perceived Risk

Summary (see Table 14) of total effect, direct effect and specific indirect effect were used to assess the mediation effect of each mediator variable.

1. Mediation analysis was performed to evaluate the mediating role of PB. The results (see Table 13) revealed insignificant ($p > 0.05$) mediating role of PB ($\beta = 0.009$, $t = 0.165$, $p = 0.869$) did not mediate the relationship between AC and AQ.
2. Mediation analysis was performed to evaluate the mediating role of PC and PB on the relationship between DQ and AQ. The results revealed insignificant ($p > 0.05$) mediating role of PC ($\beta = -0.007$, $t = 0.253$, $p = 0.800$) and PB ($\beta = -0.014$, $t = 0.166$, $p = 0.868$) did not mediate the relationship between DQ and AQ.
3. Mediation analysis was performed to assess the mediating role of PR and PC on the relationship between CP and AQ. The results revealed insignificant ($p > 0.05$) mediating role of PR ($\beta = 0.022$, $t = 0.308$, $p = 0.758$) and PC ($\beta = 0.014$, $t = 0.292$, $p = 0.771$) did not mediate the relationship between CP and AQ. Also PR and PC ($\beta = 0.012$, $t = 0.310$, $p = 0.757$) did not mediate the relationship.
4. Mediation analysis was performed to assess the mediating role of PR and PC on the relationship between LA and AQ. The results revealed insignificant ($p > 0.05$) mediating role of PR ($\beta = 0.015$, $t = 0.289$, $p = 0.773$) and PC ($\beta = -0.003$, $t = 0.182$, $p = 0.855$) did not mediate the relationship between LA and AQ. Also PR and PC ($\beta = 0.008$, $t = 0.307$, $p = 0.759$) did not mediate the relationship.
5. Mediation analysis was performed to assess the mediating role of PC on the relationship between PR and AQ. The results revealed insignificant ($p > 0.05$) mediating role of PC ($\beta = 0.025$, $t = 0.316$, $p = 0.752$) did not mediate the relationship between PR and AQ.

6. Mediation analysis was performed to assess the mediating role of PR on the relationship between CP and PC. The results revealed significant ($p < 0.001$)

mediating role of PR (β = 0.237, t = 4.053, p = 0.000). Perceived Risk of BD was found to be a significant mediator on the relationship between CP and PC.

7. Mediation analysis was performed to assess the mediating role of PR on the relationship between LA and PC. The results revealed significant (p < 0.05) mediating role of PR (β = 0.161, t = 2.462, p = 0.014). Perceived Risk of BD was found to be a significant mediator on the relationship between LA and PC.

Table 14: Mediation analysis

	Relationship	Total effect			Direct effect		Specific indirect effect			
		β	T	p value	β	p value	Relationship	β	T	p value
1.	AC -> AQ	0.087	0.697	0.486	0.078	0.533	AC -> PB -> AQ	0.009	0.165	0.869
2.	DQ -> AQ	-0.085	0.840	0.401	-0.064	0.597	DQ -> PC -> AQ	-0.007	0.253	0.800
							DQ -> PB -> AQ	-0.014	0.166	0.868
3.	CP -> AQ	0.204	1.721	0.085	0.156	0.130	CP -> PR -> AQ	0.022	0.308	0.758
							CP -> PC -> AQ	0.014	0.292	0.771
							CP -> PR -> PC -> AQ	0.012	0.310	0.757
4.	LA -> AQ	0.277	2.424	0.015	0.258	0.048	LA -> PR -> AQ	0.015	0.289	0.773
							LA -> PC -> AQ	-0.003	0.182	0.855
							LA -> PR -> PC -> AQ	0.008	0.307	0.759
5.	PR -> AQ	0.071	0.492	0.622	0.046	0.753	PR -> PC -> AQ	0.025	0.316	0.752
6	CP -> PC	0.533	5.649	**0.000**	0.296	**0.005**	CP -> PR -> PC	0.237	4.053	**0.000**
7	LA -> PC	0.096	0.905	0.365	-0.065	0.472	LA -> PR -> PC	0.161	2.462	**0.014**

Note: AC - Absorptive Capacity, AQ - Acquisition Intention, CP - Competitive Pressure, DQ - Data Quality, ES - External Support, LA - Level of Awareness, LF - Leadership Focus, PB - Perceived Benefits, PC - Perceived Cost, PR - Perceived Risk

4.7 Results of the model

Figure 21 illustrates the results of the final research model (see Annex II for the same enlarged model)

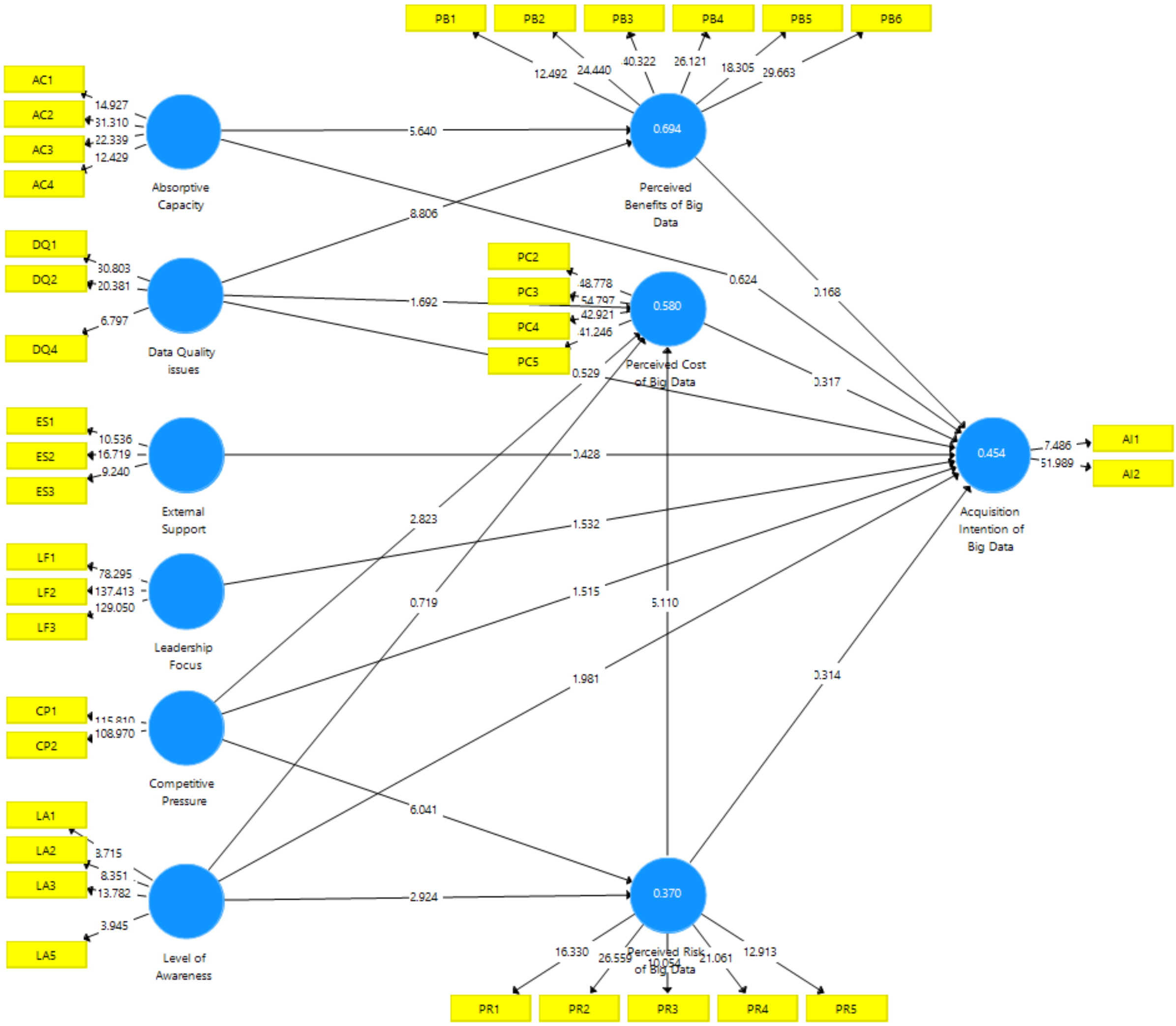


Figure 21: Results of the research model

4.8 Summary

SmartPLS 3.3.5 software was used to evaluate the data. Constructs were analyzed using the threshold values of factor loadings, Cronbach's alpha, CR and AVE higher than 0.7, 0.7, 0.7 and 0.5, respectively. Three items (DQ3, LA4 and LA6) were removed which did not meet the threshold requirement. Satisficed constructs meet the threshold values which demonstrate the convergent validity is acceptable.

Discriminant validity was evaluated using cross loadings, Fornell & Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio of correlations method. All the above criterions were satisfied for this research. Thus, discriminant validity is satisfactory for the model. Updated measurement model was then used to analyze the structural model. Finally, it identifies the mediation effect of three mediator variables: perceived benefits of Big Data, perceived cost of big data and perceived risk of big data.

CHAPTER 05: CONCLUSION

Big data applications have increased the efficiency and effectiveness of organization by every possible way. Although construction industry is very significant as it provides considerable amount for country's gross domestic product (GDP), they are still lagging in the usage of Big Data applications. This study is an initial investigation of the big data adoption intention in Sri Lankan construction sector organizations.

According to the results of the questionnaire, it has identified that only few organizations are using BD technologies such as BD storage systems, BD processing tools and BDA. The respondents have specifically mentioned that these technologies are only in the research stage and do not use in the organizational processes.

Nine core critical factors were identified using professional journal articles by in depth literature analysis. According to the literature review organizational absorptive capacity, organizational data quality issues, external support from vendors, leadership focus on innovation, competitive pressure, level of awareness and understanding on innovation, perceived benefits of BD, perceived cost of BD and perceived risk of BD has identified as the determinant that influence the acquisition intention of BD.

Among the nine factors considered, only level of awareness and understanding has significant effect on acquisition intention of BD. Other factors, organizational data quality issues, absorptive capacity, external support, leadership focus, competitive pressure, perceived benefit of BD, perceived cost of BD and perceived risk of BD have insignificant effect on acquisition intention. The possible reason for the insignificant effect of perceived benefit of BD is that the main concept and the technology are new to the respondents.

When consider the effect on perceived benefit of BD, organizational data quality issues has a significant impact while absorptive capacity has significant but negative effect. Competitive pressure and perceived risk of BD has a significant effect on perceived cost of BD. But organizational data quality issues has significant but negative effect on perceived cost of BD while level of awareness has insignificant effect. According to the findings, competitive pressure and level of awareness has a significant effect on perceived risk of BD.

Second objective was answered by analyzing the mediation effect of three mediations variables. Perceived benefit of BD, perceived cost of BD and perceived risk of BD was identified as the mediation variables of the research model. Different relationships were identified based on the literature review. According to the mediation analysis, only perceived risk of BD act as mediator. It mediates the relationship between level of awareness and perceived cost of BD. The direct relationship between level of awareness and perceived cost of BD was identified as an insignificant from the results obtained. According to the mediation analysis, when perceived risk of BD acts as the mediator, it has identified a significant relationship between above two variables. Therefore it can conclude that level of awareness significantly affects the perceived cost of BD in the presence of perceived risk of BD. Further perceived risk of BD mediates the relationship between competitive pressure and perceived cost of BD. According to the mediation analysis between the identified relationships, perceived benefits of BD and perceived cost of BD did not mediate the relationships. Therefore, other two mediators, perceived cost of BD and perceived benefits of BD presents insignificant relationships in mediation role.

Consequently, a model was developed to identify the factors that affecting on acquisition intention of BD services in the construction industry (See Annex II).

5.1 Contribution to research

This research expands the awareness of the determinants affecting on acquisition intention of BD technologies in construction industry. This research fills a major gap by connecting the modern technologies and construction industry. Although there are many studies considering BD and other major industries, there is a lack of research on BD and construction industry. Since construction industry is different from other industries (such as telecommunication, healthcare, financial service, manufacturing, retail etc.) in terms of various different factors, this research aimed to explore the crucial factors applicable on acquisition intention, particularly in Sri Lanka.

This research provided a sole and unique model to identify the acquisition intention of BD adoption and also to identify the mediating role of the benefit, cost and risk of the BD. Identification of these determinants and the model entitle the expansion of empirical studies to identify the correspondence of these determinants.

5.2 Contribution to practice

In addition to contribution to research, this study provides important business implications for organizations regarding effectively acquisition of BD technologies. This research presents the insights of crucial determinants that effect on acquisition intention of BD in construction industry. Aldo it provides the potential impact of those determinants on acquisition intention and consequently reach better organizational performance.

Managers or the decision makers of organizations can use this research model as a baseline to assess the acquisition intention. This model can use during both implementation process and post adoption of BD technologies. The findings of this research layout guidance to decision makers who seek to leverage BD initiatives at a organizational level.

5.3 Limitations and Future Research

This study has some limitations which will also become the baseline for the future research studies. When considering the data collection, in previous studies, respondents have limited to the people who have experienced with BD technologies. Also some researchers have identified the respondents from the organizations which already use BD technologies. As Sri Lankan construction industry is still at the early stage in digitalization, this research considered respondents with experience in modern technologies. And also respondents are limiting by the level of knowledge they poses. Even though there were several limitations most of the respondents were from the organizations which do not use any BD technology even at the research and development level. Future studies can consider about these implications and consider the respondents from the organizations that already use BD technologies for business processes or at research level.

Secondly this research evaluates the research variables based on the managers' perceptions which can leads to some level of subjectivity. Nevertheless, targeted respondents are assumed to be the leading decision makers for innovation. Further studies can consider about different level of respondents by gaining the maximum scope of the research.

Thirdly, the area of data collection is based on Sri Lanka. This research does not enclose different geographical locations. Sri Lankan construction industry is far more behind in technology adoption. Further studies are required in several locations such as highly technological evolutional areas in order to generalize and validate the findings of this research.

Fourthly, in the process of data collection, this research does not consider about different software providers. Thus, it could possibly create common method bias issue. Therefore, future research may appraise more than one respondent from each organization using several different software packages.

Finally, the strategy of this research accompanies a quantitative research strategy to identify the determinants effects on acquisition intention of BD. Future research may use qualitative research strategy such as Delphi technique to identify and validate the findings. Further it can combine both quantitative and qualitative techniques in order validate the research model.

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Annexure I - Questionnaire

Section 01: General Information

1. Please select the Sector of your Organization
    - Government
    - Semi-Government
    - Private
    - Foreign
    - Multi-National

2. Please select the type of your organization
    - Contractor firm
    - Consultancy firm
    - Construction Design firm
    - Construction Service/ material supplier
    - Other

3. Please select the Grade of your Organization
    - C1
    - C2
    - C3
    - C4
    - C5 or below
    - Other please specify

4. Please select your Designation
    - CEO/Owner/ Head of Organization
    - Senior Management/ Director/ Head of Department
    - Middle Management/ Senior Engineer/ Senior Manager / Senior QS
    - Executive/ Engineer/ Manager/ QS
    - Other please specify

5. Please select all the technologies uses in your Organization
    - Building Information Modeling (BIM) software
    - Enterprise Resource Planning (ERP) system
    - Document Management System (DMS)
    - Building Management System (BMS)
    - Building Performance Simulation (BPS) software
    - Building Automation System
    - Estimating or Planning software
    - Modeling or Designing software
    - Internet of Things (IoT)
    - Smart Building technology
    - Artificial Intelligence (AI)
    - Business Intelligence (BI)
    - Cloud Computing
    - Augmented reality (AR)
    - Virtual Reality (VR)
    - Mobile Apps
    - Networking systems
    - Other Please specify

6. Your experience with modern technologies/ software/ systems

- No experience
- Less than 1 year
- 1 - 3 years
- 3 - 5 years
- More than 5 years

7. Rate your highest level of knowledge on any of above mentioned modern technology/ system/ software

- 1 - Very Poor
- 2 - Poor
- 3 - Fair
- 4 - Good
- 5 - Excellent

8. Does your organization use any of the following Big Data Services/ technologies?

	Yes	No	No Idea	Plan to adopt in the near future
8.1 Big Data Storage System	○	○	○	○
8.2 Big Data Processing tools/ techniques	○	○	○	○
8.3 Big Data Analytics (BDA)	○	○	○	○

Help,

8.1 Big Data Storage System (ex: Hadoop distributed file system [HDFS], NoSQL databases, etc)

8.2 Big Data Processing tools/ techniques (ex: Apache Hadoop, Apache Spark, etc)

8.3 Big Data Analytics (BDA) (ex: Tableau, Splunk, Spark, Microsoft Power BI, etc)

Section 02: Factors

This section identifies the factors that effect on the acquisition intention of Big Data services in the construction industry. This research has identified several factors such as; 1. Level of awareness and understanding, 2. Organizational absorptive capacity, 3. Organizational Data Quality issues, 4. Perceived benefits of Big Data services, 5. Perceived Cost of Big Data services, 6. Perceived Risk of Big Data services, 7. Leadership focus, 8. External support from vendors & 9. Perceived competitive pressure. This page is to identify the following factors 1/9 - Level of Awareness and Understanding - Identifies the awareness level and understanding on Big Data 2/9 - Organizational Absorptive Capacity - Identifies the Absorptive capacity of construction industry employees on Big Data 3/9 - Organizational Data Quality issues - Identifies the quality measures of construction data 4/9 - Perceived Benefits of Big Data services - Identifies the positive results that are caused by Big Data Services acquisition

1. Are you aware of the following terms?

	5 - Extremely Aware	4 - Moderately Aware	3 - Somewhat Aware	2 - Slightly Aware	1 - Not Aware at all
1.1 Big Data	◯	◯	◯	◯	◯
1.2 Big Data Analytics	◯	◯	◯	◯	◯

Help,
5 - Extremely aware - I possess proficiency and knowledge on this concept

4 - Moderately aware - I can adequately understand this concept

3 - Somewhat aware - I am aware of this concept but only to some extent

2 - Slightly aware - I have heard this term but not aware of its meaning

1 - Not aware at all - I have never heard this term

2. Please rate the following questions as per your awareness and understanding

(Factor 01 / 9 - Level of Awareness and Understanding)

(7 = Strongly Agree … 1 = Strongly Disagree)

	7	6	5	4	3	2	1
2.1 “Big Data” can be identified by 3V’s; Volume, Velocity, and Variety							
2.2 I have identified that our organization deals with different formats of data (doc, ppt, pdf, dwg, jpeg, rvt, etc.)							
2.3 Data comes to our organization from several data sources (financial systems, email, IoT, GPS, mobile apps, BMS, supply chain, etc.)							
2.4 I have never heard of any relationship between Big Data and Construction							

Help;

2.1 Volume - the size of the data, Velocity - speed of incoming and outgoing data, Variety - sources and types of data

3. Please rate the following questions

(Factor 02 / 9 - Organizational Absorptive Capacity)

(7 = Strongly Agree … 1 = Strongly Disagree)

	7	6	5	4	3	2	1
3.1 Our organization provides training and guidance on new technologies							
3.2 Our organization conduct researches on new technologies and implement those technologies in construction projects							
3.3 Our organization has internal/external subject matter experts in, handling data/ data science							
3.4 Our organization deals with internal/external, IT departments/organizations in handling and analyzing large data sets							

4. Which method/ methods does your organization use to assess, control, and improve the quality of organizational data?

(Factor 03 / 9 - Organizational Data Quality issues)

- Manual Methods
- Data Quality Management (DQM) system
- Do not use any method
- No Idea
- Other, please specify

5. Please rate the following questions

(Factor 03 / 9 - Organizational Data Quality issues)

(7 = Strongly Agree … 1 = Strongly Disagree)

	7	6	5	4	3	2	1
5.1 Our organization receives data timely (real-time project updates) for faster decision making							
5.2 All the departments in our organization inputs data with no omissions							
5.3 Our company spends a considerable amount of time and staff on identifying, validating, and fixing errors in datasets							
5.4 Our organization use standard formats to store and present data consistently5.4 Our organization use standard formats to store and present data consistently							

6. Please rate the following questions

(Factor 04 / 9 - Perceived Benefits of Big Data)

(7 = Strongly Agree … 1 = Strongly Disagree)

	7	6	5	4	3	2	1
6.1 Our company uses data storage system to store all the data (historical data, lesson learned data, real-time data, and streaming data)							
6.2 Our company uses both documented and real-time data for accurate decision making							
6.3 We use all the past data (historical, lesson learned, etc) to identify meaningful data patterns (cost, resources, risk)							

	7	6	5	4	3	2	1
6.4 We make accurate predictions (in terms of cost, budget, risk) for future projects using previously identified data patterns							
6.5 Our company processes data to gain in-depth insights (to increase organizational performance)							
6.6 Our company successfully utilize all the available data to gain a competitive advantage							

Section 2.2: Factors

This section identifies the following factors,

5/9 - Perceived Cost of Big Data services - Identifies the organizational readiness to acquire Big Data

6/9 - Perceived Risk of Big Data services - Identifies the potential uncertainty

7/9 - Leadership Focus - Identifies the support and focus of leaders

8/9 - External Support from vendors - Identifies the support provided by IT vendors

9/9 - Perceived Competitive pressure - Identifies the pressure by competitors on Big Data adoption

7. Please rate the following questions

(Factor 05 / 9 - The perceived cost of Big Data services)

(7 = Strongly Agree … 1 = Strongly Disagree)

	7	6	5	4	3	2	1
7.1 Our company has evaluated the initial purchasing cost of some/all Big Data services							
7.2 Our company has the financial feasibility to adopt Big Data services (fully or partially)							
7.3 Our company has the financial feasibility to invest in operational costs and training costs of Big Data services							
7.4 Our company can fulfill the IT infrastructure requirement for Big Data services							
7.5 Our company has the financial feasibility to address Data Security and Data Privacy issues that may arise due to Big Data services							

8. Please rate the following questions

(Factor 06 / 9 - Perceived Risk of Big Data services)

(7 = Strongly Agree … 1 = Strongly Disagree)

	7	6	5	4	3	2	1
8.1 Big Data services create access to the organization's sensitive data							
8.2 Big Data services create concerns on Data ownership							
8.3 There is a potential of failure and losses during the implementation process of Big Data							
8.4 Big Data services create concerns on data security and privacy							
8.5 The need to outsource Big Data services creates risks through excessive dependency on vendor							

9. Please rate the following questions

(Factor 07 / 9 - Leadership Focus)

	7	6	5	4	3	2	1
9.1 Our leaders promote Big Data services as a strategic priority							
9.2 Our leaders support for Big Data services initiatives within the organization							
9.3 Our leaders show great interest in the implementation of big data services							

10. Please rate the following questions

(Factor 08 / 9 - External support from vendors)

	7	6	5	4	3	2	1
10.1 Vendors actively market Big Data services adoption							
10.2 Vendors can provide required training for Big Data services adoption							
10.3 Vendors can provide technical support for Big Data services adoption							

11. Competitors in our industry use Big Data services

(Factor 09 / 9 - Perceived competitive pressure)

- Yes
- Uncertain
- No

12. Please rate the following questions
(Factor 09 / 9 - Perceived competitive pressure)

	7	6	5	4	3	2	1
12.1 Our organization would acquire Big Data services in response to what competitors in the industry are doing							
12.2 Our choice to acquire Big Data Services would be strongly influenced by what competitors are doing							

Section 3: Acquistion intention

AQ. Please rate the following questions

(Aquisition Intention)

	7	6	5	4	3	2	1
AQ1: I recommend to acquire Big Data Services to our organization in the near future							
AQ2: Our organization may acquire Big Data services in the near future							

Annexure II – Research Model