Big Data Analytics Socio-Technical Systems on Strategic Decision Making and Organisational Performance: Case of Saudi Arabian Higher Education.

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Certificate of Original Authorship

I, **Maher Mohammed Aseeri** declare that this thesis is submitted to fulfil the requirements for the Doctor of Philosophy (Information Systems) award in the School of Professional Practice and Leadership Faculty of Engineering and IT at the University of Technology Sydney. This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Abbreviation Descriptions

Abbreviation	Description
ACC	Accepting big data analytics new technologies
ADA	Adapting to new big data analytics technologies
BDA	Big Data Analytics is the process of analysing a huge amount of big data to gain insights from analysed big data
BDPs	Big Data Analytics Performers include Information Technology staff and Data Scientists
ITs	Information Technology staff that include academic and non-academic Staff.
DS	Data Scientist
BDT	Big Data Analytics Tasks
BDS	Big Data System Quality, i.e. big data security, privacy, and quality
BDS	Big Data Security
PRI	Big Data Privacy
QUA	Big Data Quality
ITSp	IT Staff for privacy
ITSs	IT Staff for security
SACS	Saudi Authority of Cyber Security
DE	Data Engineer
SG	Security in General
DSQ	Data Scientists for Big Data Quality
OCBDSQ	Organisational Culture on Big Data System Quality
OCS	Organisational Culture on Big Data Security
OCP	Organisational Culture on Big Data Privacy
OCQ	Organisational Culture on Big data quality
OCTM	Organisational Culture on Top Management
OCIT	Organisational Culture on IT staff
OCDS	Organisational Culture on Data Scientists
OCWS	Organisational Culture on whole Staff
OCTM	Organisational Culture on Top Management Staff
OCBDTs	Organisational Culture On Big Data Tasks
OCDV	Organisational Culture on Data Visualisation
OCIDM	Organisational Culture on Improving Decision-Making
DES	Improving Decision making

OP	Improving University Performance
OCOP	Organisational Culture On Improving University Performance
OCBV	Organisational Culture in creating Business Values
STO	Storing Big Data
ANA	Analysing Big Data
VIS	Visualising Big Data
FND	Financial Decisions
STD	Strategic Decisions
ACD	Academic Decisions

Doctoral Conference Papers and Journals to Date

The research articles that have recently been published or are being reviewed are listed below.

• Aseeri, M. & Kang, K. "Organisational Culture and Big Data Socio-Technical Systems on Strategic Decision Making: Case of Saudi Arabian Higher Education", International Journal of Educational Technology in Higher Education" 2022 [Final Decision].

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• Aseeri, M. & Kang, K. "Big Data Analytics in Saudi Arabian Higher Education: Human and Organizational Culture perspectives, 38th IBIMA Conference on November 2021 Seville, Spain.

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Abstract

Big Data Analytics (BDA) is an emerging technology that has revolutionised varied fields such as Higher Education Institutions (HEIs), healthcare, governments, and private sectors. BDA technologies allow firms to quickly access, analyse and visualise a variety of big data that could improve executives' decision-making. As a result, improving decision-making will lead to enhance overall organisational performance. Although a significant amount of research exists on BDA in higher education institutions, studies that combine socio-technical aspect that support BDA in Saudi HEIs is lacking. In particular, applying mixed methods to explore the influence of socio-technical aspects that support BDA in Saudi HEIs. Hence, this research investigates the socio-technical subsystem that supports big data analytics and its role in improving top management decisions and the overall performance of Saudi HEIs. This research applied socio-technical theory for the proposed model based on the ontological postpositive for the quantitative method and the interpretivism paradigm for the qualitative method.

Considering the research gap provided above, this study applied a mixed methods approach for data collection. Besides, we applied a cross-sectional survey for the quantitative data, whereas the qualitative data applied semi-structured interviews. The sample population involved the IT staff and data scientists, representing the big data performers (BDP) and top management in the Saudi HEIs. Quantitative data was collected using validated scales of previous studies, and the hypotheses were evaluated using PLS-SEM. Consequently, qualitative data were analysed using N-Vivo 12 pro, and a thematic analysis technique was applied, which formed themes and patterns that were then combined with the outcomes of the "quantitative results".

In light of the findings, the PLS-SEM analysis conducted to test the hypotheses highlighted the significance of BDP on Big Data Systems (BDS), i.e., security, privacy, and quality. However, the results revealed the insignificance of organisational culture in big data systems (BDS), although having a positive value. Nonetheless, the organisational culture significantly impacted BDP, implying the influence of a data-driven culture and supportive top management on the workforce's attitude towards BDA-related change and skill development. Besides, the social and technical subsystems of the BDA— the BDS and BDP— are significantly correlated, along with their correlation with strategic decision-making.

The study's implications comprised insights guiding the managers and policymakers to acknowledge the importance of organisational culture (hierarchical, adhocratic, market, and clan) while strategising the implementation of BDA and its systems and developing training modules for its BDP accordingly. Furthermore, the study's application of the socio-technical systems (STS) theory would help practitioners and policymakers address the existing challenges in the OC, BDS and BDP to ensure efficient BDA generating quality, certain and error-free data supporting high-end decision-making.

Key Words: Big Data Analytics, Big Data Systems, Socio-Technical Theory, Saudi Arabia Higher Education, Organisational Culture, Strategic Decision-Making, Organisational Performance.

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CHAPTER 1

Introduction

1.1 Introduction

This chapter highlights the problem background and context of the current research. It presents the aims & objectives, identifies the research gaps and states the research questions and supporting methodologies in line with the identified aims. The key aim of this research was to explore the socio-technical influence of BDA on top management decision-making and its subsequent impact on the performance of Saudi Arabian HEIs. Based on the literature review and after analysing the collected data, the results offer critical insights that justify the significance and contribution of this study. In the end, the research process is pictorially presented along w a thesis structure that outlines each chapter's summary.

1.2. Research Background and Problem Context

The ongoing developments in the field of Information and Communication Technologies (ICTs) have fostered the pace of cutting-edge developments and innovations of the modern- businesses. The ICTs have not only complemented the organisational ability to analyse and draw insights from the available data for making strategic business decisions, but these have additionally helped organisations stay competitive in the global business environment (Mikalef et al. 2019). This, however, necessitates the application of Big Data Analytics (BDA) which requires organisations to take into account and leverage the available big data before implementing new policies and programs or undergoing structural changes.

Big Data concept can be seen as a huge amount of data that could not be handled using traditional tools (Hassanien & Darwish, 2020). Big Data is typically described by three Vs i.e., Velocity, Variety and Volume (Xu & Duan, 2019). Besides, big data is considered an as enormous collection of data that is challenging to manage, regulate or analyse in a conventional manner (Shahat 2019). Large or increasing amounts of data are referred to as volume, Terabytes and petabytes are units used to describe the size of big data (Herschel & Miori, 2017) and high-capacity storage systems are needed to handle such a volume of data. Variety relates to the heterogeneity of data, which can be collected in structured or unstructured formats. Velocity relates to big data access speed. In a real-time context, the data are practically present (Hassanien & Darwish, 2020). The three Vs mentioned above have been expanded into many Vs. For instance, Big Data was categorised as the 5Vs — Velocity, Veracity, Volume, Variety and Values (Younas, 2019). Also, Saggi & Jain (2018) included two additional Vs to make it seven: Valence & Variability.

Advances in Information and Communication Technologies (ICTs) have greatly aided the creation of innovative data creation and management technologies for global businesses, thereby enhancing digital technologies through the creation of a variety of large volume of data that can be accessed at high speed (Nick 2018). Big Data is predicted to double in size every 2 years, and so are its anticipated benefits. Thus, it has become crucial for businesses to make the most of BDA in the current era of digital data innovations to make smart decisions and gain a competitive advantage. In recent years, BDA has been gaining popularity in the corporate world. Various firms are now seeking to implement BDA with the expectations that it will enhance their decision-making abilities and corporate effectiveness (Mikalef et al., 2019). Beside big data, Big Data Analytics (BDA) can be defined as a process of capturing, analysing and visualising big data for making effective decisions that enhance organisational performance (Fosso Wamba et al., 2018). It can also be defined as the capacity of an organisation to organise, manage, and implement Big Data (BD) resources efficiently and strategically with an aim to enhance performance and decision-making processes (Shamim et al., 2020).

Accordingly, the growing implementation of BDA is associated with business advancement, effective decisions and firm performance, particularly when firms relish a culture of making effective decisions (Wong, 2021). In addition, BDA has been noted to promote entrepreneurship (Dubey et al., 2019) and dynamic firm performance abilities (Wamba et al., 2017). Furthermore, as the primary big data source, social media analytics supports large-scale marketing strategies (Dong and Yang 2018). Given that BDA-based innovations are more common in developed countries, the developing nations have now begun to recognise the social and economic benefits of harnessing big data for improved analysis and complex problem-solving, particularly in healthcare, education, agriculture, economics & finance. In this regard, Saudi Arabia, a developing country, acknowledges the significance of modern technologies such as Cybersecurity, the Internet of Things, Artificial Intelligence, and Big Data Analytics (CITC, 2016). Because of the growing interest in these fields, the importance of BDA is widely recognised in both public and private sector organisations.

Big data analytics has dramatically increased in higher education, allowing academics to examine subject groups without necessarily relying on difficult measurement techniques. Emerging big data technologies have now made possible the inexpensive creation and collection of data for various scientific purposes (Mayer-Schönberger, 2016), the pressure and resources of higher education institutions and its role in empowering artificial intelligence to improve overall performance (Bag et al., 2021). Given the large amount of educational data created as part of online course materials, guidelines and learning process management in addition to access to the student records (Khedr et al., 2019), such data can be utilised,visualised and analysed using the appropriate software tools to determine students' learning styles and needs along with other trends and patterns in order to aid future academic planning and decision making (Greer and Mark, 2016; Holland, 2019). Teachers with little subject experience or expertise can benefit from visualisation outputs to self-help themselves in terms of understanding and interpreting student learning needs (Ong, 2015). In view of this, educational big data technologies could be leveraged to enhance the student learning experience and augment the quality of educational programs (Khedr & Idrees 2017)

In this regard, the higher education sector has significantly evolved owing to the development of digital teaching & learning management technologies, especially in academically advanced countries (Alhamed, 2017). Recently the COVID-19 pandemic made it indispensable to adopt learning management platforms in the higher education sector of both developing and developed countries (Rehman, 2021). Moreover, with the global shutdown of Higher Education Institutions (HEIs) and discontinuation of face-to-face classes for an extended period, it triggered the adoption of virtual, online and remote learning methods that were aided by a Learning Management System (LMS) created for the purpose (Khedr et al., 2019; Auf & Hamdi, 2022; Ssemugenyi & Seje, 2021; Zhou et al., 2022). Consequently, BDA is being increasingly viewed by higher education institutions globally as a critical dimension for improving learning analytics and user experience (Amare & Simonova, 2021; B&R, 2016; Chaurasia et al., 2018; Ifenthaler & Gibson, 2020; Mago & Khan; Picciano, 2012; & Kumar, 2019).

While BDA enhances decision-making at various levels within an organisation (Janssen et al., 2017; Monino, 2021; Osuszek et al., 2016; Shamim et al., 2020; Sherzod & Liu, 2020), the need to adopt BDA is often ignored in the HEIs of developing countries (Ashaari ,2021; Amare & Simonov 2021). Moreover, the adoption pace of new technologies differs significantly, specifically, when it comes to developed and developing countries (Cheng et al., 2021; Kabalisa & Altmann, 2021). In addition, there is also an inconsistency governing the evaluation of the ICT impact in the case of developed and developing countries (Cheng et al., 2021). In the light of this, a country's technological maturity and technological adoption trends form the basis of socio-economic progress and explain the difference in approach. For instance, the country like China focuses on mass production for economic outcomes. On the other hand, less developed economies pursue a national plan for socio-economic and infrastructural development while striving to attain technological maturity (Kabalisa & Altmann, 2021). Since the barriers to the adoption of big data technologies are mostly social, cultural and environmental in nature and also contextually specific to a country (Alalawneh & Alkhatib, 2021), a developing country such as Saudi Arabia which recently took an interest in the emerging technologies as part of its national transformation plans were chosen for this study. Thus, in the wake of the ever-increasing effectiveness of the BDA applications in the business organisation of developed countries, the study examined the socio-technical influence of BDA on top management decision-making and its subsequent impact on the performance of Saudi HEIs.

1.3. Research Aim & Objectives

This study investigated the role of socio-technical factors in utilising BDA for senior management decision-making in Saudi Arabian HEIs. The specific aims & objectives were to:

a) Evaluate the effect of Big Data Analytics (BDA) performers and Organisational Culture (OC) on Big Data System (BDS) quality and the successful execution of Big Data Technologies (BDT).

b) Examine the influence of Organisational Culture (OC) on Big Data Systems (BDS), Big Data Analytics Performers (BDP) and the successful execution of Big Data Technologies (BDT).

c) Evaluate the effect of organisational culture on top management decision-making and the performance of Saudi Arabian universities.

d) Evaluate the effect of BD system quality on top management decision-making in Saudi Arabian universities.

e) Evaluate the effect of BD-driven decision-making on the performance of Saudi Arabian universities.

f) Examine the influence of Big Data Analytics Performers (BDP) on improving the decision-making by executives in Saudi Arabian universities.

1.4. Key Insights and Research Gaps

In developing economies such as Saudi Arabia, Big Data Analytics (BDA) is now at the core of technological advancements in several sectors whose role is pivotal in enhancing efficiency and business performance (Dong & Yang, 2018). Expectedly, other studies such as Ashaari et al. (2021) and Janssen et al. (2017) have also indicated the role of BDA in organisational decision-making and enhancing performance. However, despite the potential benefits, studies have raised various technological, data, human and organisation culture-related issues that hinder the implementation of BDA (Alalawneh & Alkhatib, 2020; Albanna & Heeks, 2019; Appelbaum, 1997). Halford and Savage (2017) stated that one such problem is that BDA necessitates organisations to gain insights from available data, information and computational capabilities to improve organisational governance and enhance efficiency. Nevertheless, these capabilities would be least effective if the staff is not competent enough to utilise in-house ICT infrastructure, business systems, data processing & management capabilities in the creation, analysis and, production and application of meaning information for making strategic decisions and drawing key business insights (Aseeri & Kang, 2023)

Alharthi et al. (2017), Thirathon et al. (2017) point out that administrative staff rarely understand how to make the most of BDA and derive business value from the available organisational data. Thus, an organisation should hire a qualified data scientist with the required skills to best meet its data analytics needs. Another challenge faced by organisations in developing countries is that their top management either ignores or underestimates the benefits of data governance and its potential impact on managerial decisions (Alharthi et al., 2017; Mukthar & Sultan, 2017). Gerber (2018) specifically discussed the core issues faced by HR professionals while assessing BDA, and such issues primarily arise due to a lack of knowledge of big data analytics.

The effectiveness of BDA in decision-making is hampered by the lack of trained and skilled data analysts, coupled with a lack of awareness (Albanna & Heeks 2019). One of the key reasons behind this attitude is the unavailability of big data education and training framework that could be applied for building and enhancing data analytics skills for making smart business decisions and enhancing the efficiency of business processes (Fosso Wamba et al., 2016). In addition, the creative skills of the organisational staff assist in the efficient management and analysis of large amounts of data (Ahmed 2016). The rapidly changing corporate environment challenges the Saudi Arabian higher education sector, which calls for innovative ways of working (Aseeri & kang, 2021). However, the lack or little ability of the organisational members to adopt and maximise the use of ICT tools makes it difficult for such organisations to live up to fast-paced technological advancements (Wood & Leone, 2015).

Moreover, there are insufficient staff trainings to help deal with rapid technological advancements and aid complex business problems solving and decision-making (Nick, 2018). De Mauro et al. (2016) propounded that while the change theory focuses on the event's failure or success, it doesn’t consider the "people" as the main reason for the change. In this regard, Nelson &Winter (1982) opined that the technology could not be standalone applied in an effective manner without the involvement of the people and other key factors such as organisational culture and leadership.

Successful application of BDA necessitates the availability of internal resources competencies in an organisation, such as its skilled staff and data system capabilities, to aid big data-driven decision processes (Ashaari et al., 2021). Smart BD-driven decisions are not just based on access to data & information, but it is equally important to have creative people skilled enough to make sense of the available big data (Aseeri & Kang, 2022; Tulasi & Suchithra, 2016).

While BDA involves a wide range of processes and activities such as acquiring, processing, visualising and making sense of the analysed data for business decision-making (Hassanien & Darwish, 2020). Executing these activities requires a data-governance-based organisational culture. This is because the organisational culture also becomes a key barrier, especially when adopting BDA in developing countries (Alalawneh & Alkhatib, 2021). In recent years, the benefits of BDA implementation have been reported by many industries, but its implementation in the higher education sector of developing countries, especially in the scientific and performance management of HEIs is not much evident in the literature (Aseeri & Kang, 2023; Mukthar & Sultan, 2017). However, an appraisal of BDA in business organisations by Mikalef et al. (2018) revealed that the BDA not only assists in identifying strategic priority areas and core application processes, but it was seen as the key driver of the competitive advantage when adopted on a long-term basis (Tulasi & Suchithra, 2016).

In a more theoretical context, Camargo Fiorini et al. (2018) reviewed the management theory of big data. As part of a systematic review, Mohammad poor and Torabi (2018) underlined the new developments in integrating BDA into the petroleum industry. Similarly, Neilson et al. (2019) conducted a comprehensive literature review on BD in the transportation sector and revealed its benefits and impacts. Other BDA application sectors include agriculture (Kamilaris et al., 2017) and detection of electrical consumption in Egypt. Shaker, et al., (2019). However, implementing BDA in the higher education sector is still in its infancy. Especially, the adoption of BDA, when viewed from the perspective of the higher education sector of the developing countries, warrants more evaluations regarding its specific benefits (Aseeri & Kang 2022; Rialti et al., 2019).

Needless to say, the implications of BDA in higher education sector of the developed world are quite evident from the recent literature, it is, therefore, important to explore opportunities in the developing Middle Eastern economies keeping in view their varied regional, social, cultural and religious context as these factors greatly shape their beliefs governing the adoption, use and diffusion of technologies including the adoption of BDA tools & technologies.

From the viewpoint of Saudi Arabia, the adoption of BDA has been reported in healthcare (Qaffas et al., 2021), supply chain management (Alaskar et al., 2021) and banking (Almoqren & Altayar, 2016). However, the integration of BDA to aid strategic decisions and learner experience in the HEI sector is still being researched and evaluated. Besides, the demand for big data analytics has also risen in various other industries, including e-commerce, telecommunication, insurance, healthcare and construction (Ahmed et al., 2018; Dresner Advisory Services, 2017; Wang et al., 2018; Wu & Lin, 2018). Given the fact that the education sector, especially during the COVID-19 pandemic, greatly benefitted from e-learning technologies and remote teaching platforms (such as remote education, virtual teaching, online learning management systems etc.), these digital innovations, trends and practices generated an enormous amount of new data in the HEI sector (Oi et al., 2017). Teachers now have access to students' academic records, performances and learning patterns that, enable them to provide immediate feedback (Black & Wiliam, 2018). This has increased the students' motivation, and they are now satisfied by the swift and helpful comments, leading to positive and improved learning outcomes (Sheng & Bender, 2019). The timely availability of key information related to students' feedback and learning patterns has assisted teachers in effectively evaluating and subsequently improving teaching methodologies, thereby adjusting to the learning needs of their students (Khedr et al., 2019).

With the advent of various digital learning platforms, many courses are being provided based on the learners' academic and professional growth needs (Holland, 2019). The large volume of available data in many HEIs can assist in the academic planning process and forecasting future learning needs of the students, researchers and working professionals (Alkhalil, et al., 2021; Baig et al., 2020; Sorensen, 2018). BDA also allows educators to comprehend and respond to the unique learning needs of the students by enabling them to create their individualised learning plans. Students can select educational pathways based on insight from BDA. An instructor can assist the student in selecting a course or programme better suited to their learning preferences. Students feel more empowered to match their academic experiences with their interests because of a more individualised approach to education. As a result, their academic progress is optimised, along with more opportunities for professional success in future. University administrators can apply BDA to examine student dropout rates, determine the fundamental influencing factors and devise ways to increase student retention.

A study conducted by Attar (2020), Bayomy et al., (2021) highlighted that a data-oriented-organisational culture is critical to overall strategic and financial success. Similarly, Dubey et al. (2019) assert that in the era of BDA, and to increase the effectiveness of decision-making, a data-driven organisational culture fundamentally steers strategic decision-making as decisions are guided by the analytics drawn from the available data rather than the experience. It is, therefore, worthwhile to examine the factors that create a data-driven culture to make a decision and enhance overall performance, especially in the HEIs of developing countries (Aseeri & Kong, 2022; Shamim et al., 2020).

The contemporary firms of today use big data analytics to enhance operations, customer service, and individualised marketing campaigns and ultimately boost sales and profits. These firms efficiently utilise the available knowledge capabilities to create a sustainable competitive advantage over those that do not have (Aseeri & Kang, 2022; Alkhalil, et al., 2021). The same BDA benefits could be extended to the high education sector beyond learning to the strategic management of Saudi HEIs. While the benefits in learning contexts are huge, how top management in HEIs can leverage big data to support strategic educational needs is still unexplored. Consequently, senior academics & top executives in Saudi HEIs must be aware of the value of big data to reduce educational challenges in their institutions.

Yet another key factor guiding the successful utilisation of the BDA program is the socio-technical context of BDA implementation. BDA, as a social paradigm, is based on two factors. First is the human element, which consists of the people ensuring BD security, privacy and quality, including data scientists and the academic and non-academic staff. According to Alalawneh and Alkhatib (2021), people may account for 28.8% and 32.4% of big data adoption tensions in developing countries' service and public sectors, respectively. Second, the Organisational Culture (OC) consists of individuals' values or preoccupations to accept and adapt to new technological advancements (Westrum, 2004).

Culture influences how an organisation responds to innovation-based changes, such as developing big new data technologies. (Chatterjee et al., 2018; Thirathon et al., 2017). A data-oriented organisational culture would assist and build responsiveness in an organisation in terms of accepting and adapting to BDA-based technological advancements.

A BDA technical subsystem encompasses analytics functions, system security, data privacy, and overall system quality. However, the role of OC is frequently overshadowed by technical considerations, which impairs our comprehension of the interdependencies within a BDA system's social and technological components (Niederman et al., 2016). Consequently, the connection between the BD social structure and its technical system remains unexplored. As a result, the linkage between these factors needs more theoretical underpinning and empirical validations (Aseeri & Kong, 2022; Kabalisa & Altmann, 2021).

Thus, the key focus of the research, when viewed at a broader level, was to evaluate the influence of BDA's socio-technical subsystem in enabling the decision-making by the top management in Saudi HEIs. This research thus demonstrates how the BDA socio-technical systems affect top management decision-making & the overall performance of Saudi HEIs, which requires a versatile but specialised transformational approach consistent to the socio-technical environment of these HEIs. Specifically, the study explores BDA socio-technical systems in Saudi Arabian HEIs. In this regard, the social factors for BDA, including big data analytic performers (BDP) (i.e., IT staff and data scientists) and organisational culture, are evaluated. Second, the technical factors for BDA that include Big Data System (BDS) quality, security, privacy and Big Data Tasks (BDT) are examined along with their analysis, storage and visualisation. Finally, as suggested above, the BDA factors are hypothesised to evaluate how these influence the top management decision-making and the overall performance of HEIs in Saudi Arabia.

1.5. Research Questions

Given the gaps concerning BDA implementation in Saudi HEIs when it comes to making decisions at the senior executive level and its potential to augment HEIs performance, and considering the socio-technical context of BDA systems, the following research questions were proposed.

RQ1: How does the social subsystem for big data analytics affect top management's decision-making and a university's performance? We split this question into four sub-questions:

a) To what extent do Big Data Performers (BDP) influence Big Data System (BDS) and the successful execution of Big Data Analytic Tasks (BDT)?

b) To what extent do institutional structures, i.e., Organisational Culture (OC), influence Big Data Systems (BDS), Big Data Analytics Performers (BDP) and the successful execution of Big Data Analytic Tasks (BDT)?

c) To what extent do institutional structures i.e., Organisational Culture (OC), Enhancing Decision-Making DES and Improving University's Performance OP?

d) To what extent do Big Data Analytics Performers (BDP) impact the decision-making of senior management?

RQ2: How does the BDA technical subsystem, particularly BDS and BDT, affect top management decision-making in Saudi universities?

RQ3: To what extent does BD-driven decision-making influence a university's performance?

1.6. Research Methodology

This study applied mixed methods research design in which quantitative surveys were conducted followed by the qualitative semi-structure interviews. The nature of research questions, study purpose and the context informed the research design (Venkatesh et al., 2013). Investigating the extent to which the BDA socio-technical context influences the strategic decision-making and performance of HEIs necessitates a quantitative inquiry. However, the quantitative data seemed to be not sufficient enough to generate detailed insights. Consequently, a qualitative inquiry was sought to elaborate the research findings. Research in Information Systems (IS) has used a range of methodologies, each of which has shed light on a distinct aspect of the issue under investigation. Venkatesh et al. (2013) claim that Information Systems (IS) research can largely benefit from mixed method approaches as these approaches support not only the development of rich theoretical perspectives but also generate additional insights. However, these aspects are still limited in IS research.

A mixed methods research design can sequentially or concurrently undertake a qualitative and quantitative inquiry to investigate a research phenomenon (Creswell & Creswell, 2018). The mixed methods also provide a potential strategy for combining strengths and eliminating single limitations (Creswell & Plano Clark, 2018; Creswell, 2013). According to Venkatesh et al. (2016), the mixed-methods technique has three advantages when researching information systems. Firstly, it enables the researcher to address both exploratory and confirmatory research questions. Secondly, compared to a single-technique study methodology, it leads to more robust conclusions. Finally, it aids in achieving complementary or diverse points of view.

In view of the above scholarly recommendations governing the adoption of mixed methods and to address the research questions, we specifically used an exploratory sequential mixed methods approach. This exploratory mixed methods study was undertaken in two data collection phases. The quantitative study was conducted in the first phase, followed by the qualitative study in the second phase. The studies such as the ones by Venkatesh (2016), Venkatesh (2013), Greene et al. (1989) articulated why researchers engage in a mixed methods approach such as triangulation, complementarity, developmental, initiation, and expansion. In line with the recommendations of these studies, this study adopted a complementarity mixed methods approach wherein qualitative findings further elaborated and complemented the quantitative results and added new insights to address the given research problem more meaningly. According to Flick (2014), complementing the quantitative findings is critical given that the quantitative approaches have been criticised for failing to extend knowledge due to the restricted objective nature of this approach. He further argues that the single method is insufficient to generate the true realities of the phenomena being evaluated.

The study thus examined the given research problem from various scholarly perspectives. Given the fact that this study involved investigating the socio-technical aspects that influenced the technology adoption in Saudi HEIs, mixed methods approaches were considered appropriate to address the research questions posed by the study, thereby enabling the achievement of the methodological objectives of this study. A quantitative approach was used in the first stage, employing an online survey to gather responses from the participants. In the second phase, qualitative research was conducted using interviews to evaluate the reliability and validity of the quantitative results and to come up with the facts and information that remained unexplored during the quantitative phase of the research inquiry. Figure 1 illustrates these two stages of quantitative and qualitative methods applied to this study.

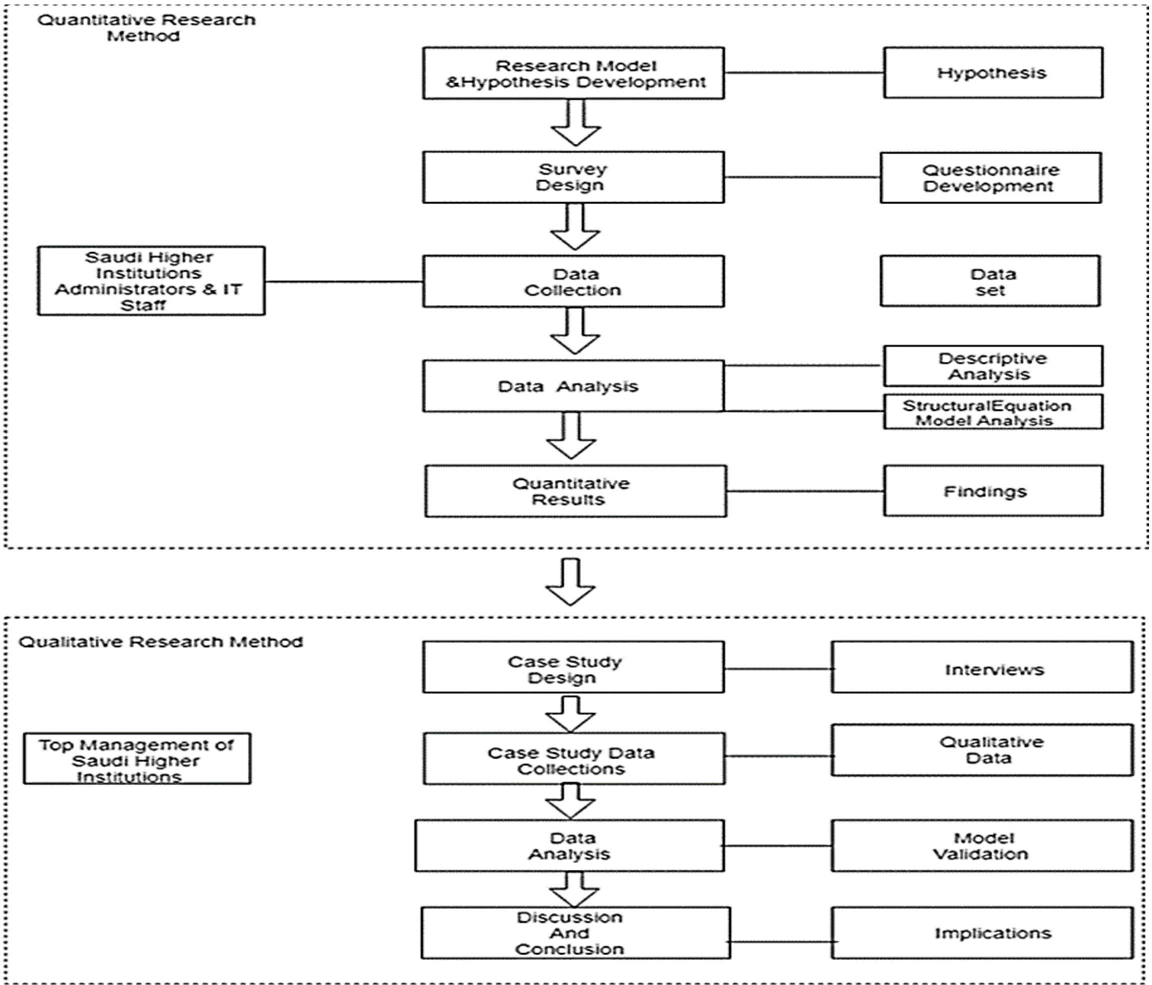

Figure 1.1. Research Design

1.7. Significance of the Study

Numerous studies have highlighted the role of big data analytics in performance and profitability (Murumba & Micheni, 2017) in many sectors, although it was initially thought that the education sector would be able to get few benefits as compared to the other sectors. To maximise the benefits of BDA in organisational performance, it is important to strategically utilise key information and data resources beyond the learning-only purposes so as enhance performance at large. Studies such as Alhamed (2017), Amare & Simonova (2021), Chaurasia et al. (2018), Daniel (2016), Muhammad et al. (2020), Murumba & Micheni (2017), Picciano (2012), Shorfuzzaman et al. (2019) have shown that the potential of new technologies in HEIs could extend their competitive advantage and business value. While potential advantages have been explored in many contexts, few efforts have been devoted to the higher education sector of developing countries such as Middle Eastern countries. For instance, only a few studies have explored BDA in Saudi HEIs (Mukthar & Sultan, 2017; Ahmed, 2016; Aljahdali & Al-Ghamdi, 2020). Insights into specific contexts could facilitate a more tailored application of BDA for optimal benefit. This thesis paves the way for a discussion on BDA implementation and BDA-induced change for operational efficiency and competitiveness in less investigated contexts.

The role of BDA in education is inevitable as benefits in the teaching and learning processes are often emphasised. Several studies have explored BDA implementation in two dimensions – educational data mining and learning analytics and both have been strongly associated with learner behaviour and learning experiences (Bamiah et al., 2018). BDA for institutional management could support a comprehensive analysis of the institutional business environment, KPIs, and success rates against benchmarked institutions. For instance, the university of Florida applies BDA for market need analysis, research and academic planning purposes, which resulted in significant time and cost savings (Bamiah et al., 2018). Thus, the BDA capabilities can significantly boost market performance and operational efficiencies regardless of the institution's size (Alkhalil et al., 2021; Gupta & George, 2016).

Consequently, while Saudi Arabia is considered among the countries that focus on big data analytics in higher education, such studies have explored individualisation, improvement and efficiency of the teaching and learning processes (Marín-Marín et al., 2019). Besides the learning experiences, BDA could improve market analysis and decision-making in HEIs (Bamiah et al., 2018). However, very little effort has been devoted to the last two opportunities. Therefore, this study delves into the strategic use of BDA in HEIs – a relatively under-explored phenomenon. Beyond the contextual and application issues discussed above, this study attempts to place the technical realm of BDA into a socio-technical systems (STS) framework. The STS framework is a powerful canvas for understanding the acceptability, application, and performance of ICTs (Coiera, 2007). It allows us to investigate various enabling factors and motivations in applying BDA in the educational management context.

This study extends the initial focus on BDA as a technical realm and then as a socio-technical phenomenon that spans across three core areas, including (i) the structure of the institutions, (ii) the tasks involved, and (iii) the big data systems and technology. However, these possibilities in the wake of BDA implementation are influenced by technology, processes and a data-driven culture (Dremel et al., 2020). Organisational culture is a source of sustainable advantage for the firm (Barney, 1986), and its significance in the successful adoption of STS frameworks cannot be underestimated. LaValle et al. (2011) argued that even though the required data and technologies are available, the BD initiatives may not come to fruition if the organisational culture negatively influences these.

Theoretically, the study adopts and validates the STS theory and framework, which increasingly becomes essential in explaining technology-induced ways of working and organisational change. Although the STS theory is theoretically grounded and empirically tested, further analysis and contextualisation will strengthen its validity and reliability and extend its application. Furthermore, this study offers additional confirmation of the generalisability of the framework by introducing new variables and the study population. The new variables provide insights into the direct and indirect interactions between the Social Factors (institutional structures and actors); Technical Factors (BD tasks and BD systems) and the Outcomes (institutional decision-making and performance). In congruence with prior studies (Dremel et al., 2020), we contend that a data-oriented organisational culture offers the structures for valuable BDA-driven decision-making and institutional performance. Consequently, our argument supports the progressively accepted beliefs that BDA can incredibly transform the way organisations do business and create value (Gupta & George, 2016; Mukthar & Sultan, 2017; Ahmed, 2016; Aljahdali & Al-Ghamdi, 2020; Fosso Wamba et al., 2017).

1.8. Overview of Key Terminologies Used in the Research

According to a survey by Ward and Barker (2013) on the definitions of big data analytics terms, all definitions agree on three aspects, i.e., the volume of datasets (size), the structure and behaviour of datasets (complexity), and the tools and techniques required (technology) (Zakir et al., 2015). Following are the definitions of some key terminologies used in this study.

Socio-Technical System is a pattern of action that combines technical and human carriers" (Ropohl, 1999, p. 191). STS is the distinction between the technological systems and its social, technical components and technology, as well as the social system and its social-technical systems (Dremel et al., 2020, p. 3). Technology-induced organisational change results from the reciprocal interrelationship between humans and technology (Ropohl, 1999), and the output is the outcome of the interaction between these two systems (Bostrom & Heinen, 1977).

Social Subsystem relates to the structures and actors (people), where structures are institutional arrangements while actors are entities with capabilities and shared culture (Dremel et al., 2020; Ropohl, 1999). The social system revolves around "Peoples' attributes (i.e., skills, & values), the relationship among people, and rewards system " (Bostrom & Heinen, 1977, p. 14).

Technical Subsystem concerns with the technologies and tasks where technologies are tools and techniques while tasks are related to data storage, analyse and visualise for making decisions (Dremel et al., 2020; Ropohl, 1999). More specifically, "the technical system is related to the processes, tasks, needed to transform the inputs to outputs" (Bostrom & Heinen, 1977, p. 14).

Big Data Analytics Performers represent the actors (i.e., the people/employees) as an element of the social system that poses certain capabilities and shared organisational values responsible for executing big data tasks and transforming big data into insights for decision-making. BDA performers include data scientists, IT personnel, and academic staff in our study context.

Big Data Tasks refer to the activities undertaken to transform big data inputs into informational outputs usable for decision-making (Saggi and Jain 2018). In the current research, big data tasks include data storage, analysis, and visualise the big data. Big data storage involves preserving data in a scalable way to support the organisation's ongoing or future data access needs. Analysing data relates to applying tools and techniques to transform data into useful insights (Siddiqa et al. 2016). In other words, it is the process of transforming data into value. Finally, visualising data generates visual representations of insights from data to allow users to understand it easily.

Organisational Culture is defined as " Systems of common assumptions which a group learns as it overcomes its internal and external integration difficulties which are carried on to new members as the key to comprehending, thinking and feeling."(Reiman & Oedewald, 2002, p. 6) . In other words, culture is the organisation's response to challenges and opportunities it faced" (Westrum, 2004, p. 22).

Big Data System Quality relates to the desired characteristics of big data analytics systems which in the settings of a big data system would include data security, privacy, and quality. Big data quality is achieved through availability, usability, reliability, relevance, and presentation quality (Batini et al., 2015). Big data security relates to ensuring data protection and access control aimed at protecting the value of the data (Kim et al., 2013), while big data privacy relates to the lawful and fair collection, use, disclosure, retention, and disposal of personal data (Fang et al., 2017). Figure 2.1 illustrates the key terminologies used in this research.

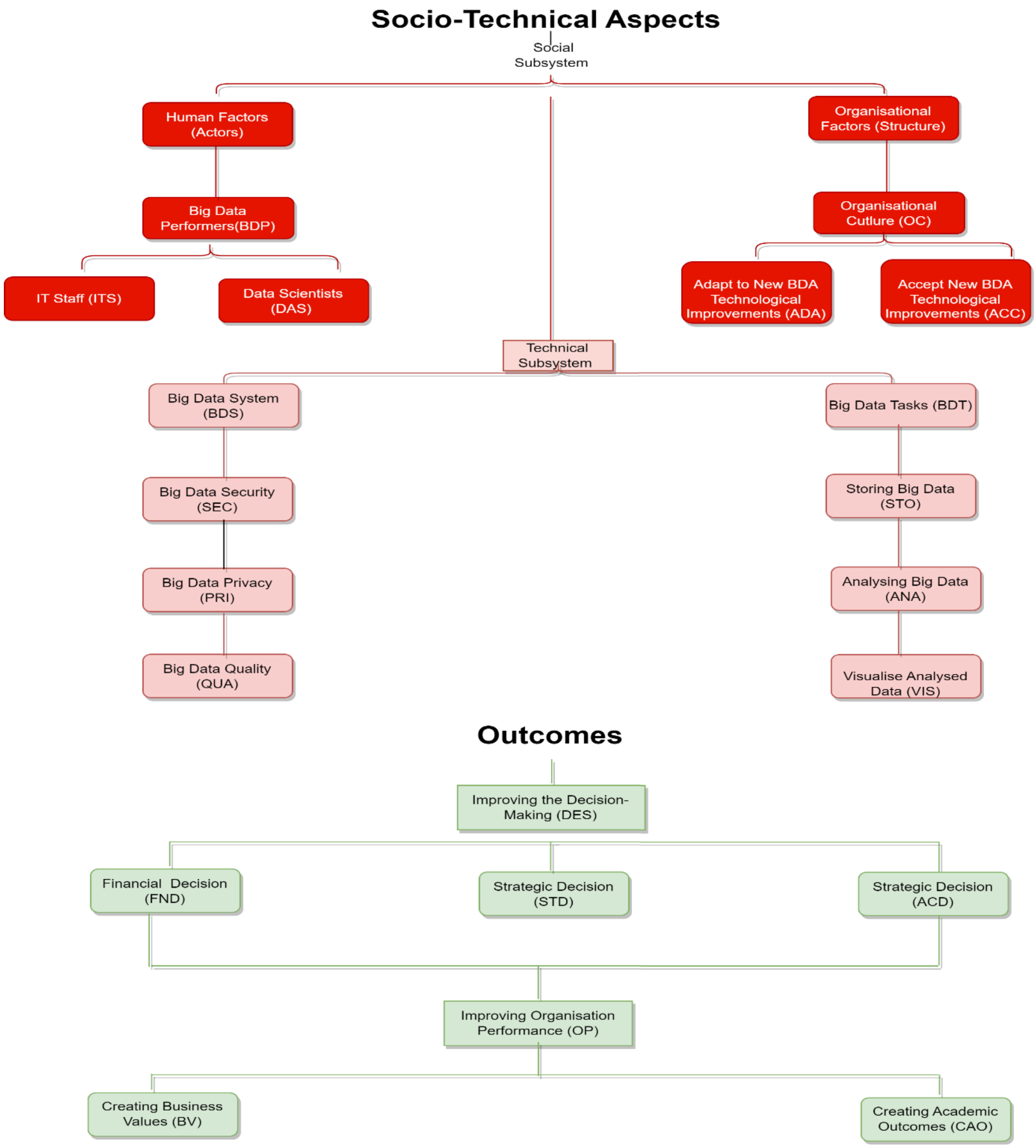

Figure 2.1. Key Terminologies

1.9. Thesis Structure

Following a conventional structure, this thesis is organised into eight chapters. The summary of each chapter is presented below.

Chapter 1: This chapter presents the problem background, objectives, research gaps, research question, methodology, significance and contribution of the study. We present our research questions, objectives, and an overview of our research design. Finally, we present a definition of the keywords underlying our study.

Chapter 2: This chapter reviews the literature on definitions and detailed theoretical discussions on big data analytics concepts & approaches, its characteristics, challenges, benefits, values, and applications. It also describes the present state of big data analytics in the HEI sector in general and the Saudi HEI sector in particular.

Chapter 3: This chapter presents the theoretical background, specifically the relevant information systems theories & literature and the other relevant frameworks that support the objectives of this study. The chapter also introduces the proposed research model, the identified research constructs, and corresponding hypotheses to test and validate the model.

Chapter 4: This chapter presents the research paradigm, research methods, quantitative and qualitative methods, research population, sampling methods, data collection instruments and techniques, and data analysis methods used in this study.

Chapter 5: The chapter analyses the results from the quantitative data collection process. Specifically, this chapter discusses descriptive and demographic analysis. Likewise, this chapter also presents a descriptive analysis of the measurement scales.

Chapter 6: This chapter presents the analysis of the proposed model using Structural Equation Modelling (SEM) with the aim of testing the suggested hypotheses. Besides the results of the analyses are also discussed in detail.

Chapter 7: This chapter discusses the qualitative data collected from the interviews. The qualitative data analyses additionally include cross-case analysis. The chapter also includes discussions on the factors that were not discerned in the quantitative phase of the study.

Chapter 8: This chapter compares the findings generated from quantitative data with those generated from qualitative data into a consistent explanation of BDA in Saudi Arabian HEIs.

Chapter 9: The chapter discusses the data, recalls the major conclusions, and the contributions of the current research along with the implications of findings, study limitations and recommendations for future studies in the Saudi HEIs context.

1.10. Chapter Summary

In this chapter, the problem background, research gaps and questions were discussed, along with the fundamental objectives and methodology of this research. The background offers a brief overview of current status of BDA, implementation gaps & challenges and explains why the study was conducted in the Saudi Arabian HEIs context. In this regard, the research objectives and questions framed for this study provided the basic guidelines for conducting the study. In addition, the motivation and importance established the research needs, and the constraints defined its scope. While this chapter presents a succinct picture of the study, the next chapter discusses in detail the core concepts, themes, frameworks, and literature studies within the domain of this research to comprehensively understand the research background, questions and proposed framework.

Chapter 2

Literature Review

2.1. Introduction

This chapter provides an overview of previous research on four key areas. These include big data analytics (BDA), socio-technical systems (STS), organisational culture (OC), and organisational performance. First, we summarise the keywords in this study which also provided the basis of the literature review. In the next section, we define Big Data Analytics, its background, characteristics, values and benefits in various contexts as presented in prior studies. This chapter also discusses the applications of BDA and the challenges encountered, with a special focus on developing countries. The chapter emphasises the state of BDA in Saudi Arabia as the scope of this study, especially in the higher education sector. Thus, we delve into BDA implementation in Saudi Arabian higher education. Finally, as a theoretical lens of this study, we review the social and technical arguments in information systems research, which later lay the foundation for our hypothesis development.

2.2. Definitions of Big Data & Big Data Analytics

Big data has different perspectives from a numerous authors. Watson (2017) described big data as massive data volume, high speed, and high variety of data necessitating new technologies and methods for capturing, processing, and visualising to enhance decisions and provide insight that allows organisations to gain a competitive edge. Cronenberg (2018), Hassanien & Darwish (2020) defined big data as the storage, governance, analysis, and vitalisation of big and complex datasets. Andrea et al. (2016) define big data as an enormous volume of data that cannot be handled using traditional data collection and storage software and tools.

Assunção et al. (2015), stated that numerous studies agree on big data's V characterisation: volumes, velocities, variety, veracities, and values. Data volume is the amount of information. The pace at which real-time data is stored, processed, and analysed is known as velocity. Variety refers to information gathered from various sources and in various formats. Veracity represents the reliability of data sources. Finally, value refers to the benefits from the data for the organisation. In summary, Big data refers to the massive volumes of data collected from a variety of sources., stored, analysed, and visualised to meet a specific organisational need or goal (Adepoju 2020).

The term “analytics” has recently been used in various contexts and has become part of the buzzword terminology that flows into emerging technology processes and applications (lia dwi jayanti 2020; Dey et al., 2018). Before defining the term analytics, we must dig into its history Zanoon, Al-Haj & Khwaldeh (2017) claimed that analytics began in 1977 when the first decision support system was created. Over time, various decision-support tools, including online analytical processing (OLAP) gained popularity (Idrees et al., 2018). Business intelligence became widely known in 1990 due to the fact of Howard Dresner, a Gartner analyst, as the founder of Business Intelligence (BI). Watson (2014) defined BI as a broad category of tools for gathering, storing, retrieving, and analysing data from various sources to assist business users in making better decisions. BI is now considered the umbrella phrase for decision-making processes enabled by data analytics.

BDA relates to gathering, storing, accessing, and analysing massive amounts of data for business needs and goals (Dey et al., 2018 ; Adepoju 2020). Similarly, Fosso Wamba, Akter, et al. (2018) described it as a comprehensive method for storing, processing, and analysing data to gain insights for long-term competitive advantages and business requirements. The five Vs are volume, variety, velocity, veracity, and value. Regarding managerial decision-making and problem-solving, BDA is the process of using the knowledge of analysing big data into insight actions for making decisions. (Liberatore et al., 2017). A more elaborated definition suggests that BDA involves analysing large datasets to find patterns, hidden patterns, industry dynamics, user habits, and other valuable data that current methods cannot traditionally analyse (Hariri et al., 2019).

2.3. Big Data Analytics

2.3.1. A Brief Background of Big Data Analytic

To appreciate big data history, we must reflect on the history of computing. The 1950 mainframes allowed centralised access to multiple users via terminals. Also, the 1950s experienced a quantitative revolution. There were attempts to effectively match enormous data sets to the computing capabilities of the computer (lia dwi jayanti 2020). For instance, William Warntz, a founder in spatial science, used census data to determine the components of US agriculture supply and demand patterns. It required extensive computational work, including laborious mathematical calculations. (Warntz, 1959). Soon after Warntz's experiment, various number of higher institutions in the US started to get their computers, including the University of Washington, which was one of the state's major "centres of calculation" for the statistical revolution.

Steve Jobs, in 1979, enhanced computational developments in terms of capacity, allowing big data to be stored and analysed. From 1998, Google was on the scene, moving data back to the server farms capable of supporting larger data volumes in specialised databases (Ruis & Shaffer 2017). Corporate data generation and collection speeds expanded significantly with the advent of the internet in the 1970s and the widespread adoption of the World Wide Web that followed in the 1990s. Besides, the big data era has gradually impacted various societies, including e-commerce, governance, and health organisations. All of the major companies—including Oracle, IBM, Microsoft, Google, and Amazon —have launched big data initiatives in recent years. Considering IBM as an instance, since 2005, the company has spent USD 16 billion on 30 big data-related acquisitions. Big data was also a topic of discussion in academia. A large data-specific issue of Nature was released in 2008. A special issue of Science on the foundational technologies of "data processing" was also released in 2011. A special issue on big data was released by the European Research Consortium for Informatics and Mathematics in 2012. Big data has been described as a new economic asset comparable to money or gold (Gartner, 2019). And this is where we are today.

2.3.2. Big Data Analytics' Characteristics

Scholars and researchers have diverse viewpoints on the characteristics of big data analytics. Some authors provided three Vs of big data. Some say there are 4 Vs, others 5, with some claiming 7 or 8 Vs. This section captures some of such perspectives—the 3 Vs. Camp (Watson 2009b; Laney 2005) characterises of big data in terms of volumes, velocities, and variety. Similarly, Apple & Steven (2017) explained the big data characteristics as volume, velocity, variety, and added variability to denote the need for scalable hardware and software for effective archiving, processing and analysis. More 3 V's. Consensus (Thirathon et al., 2017; Mckibbin & Member, 2019; Saggi & Jain, 2018; Dey et al., 2018; Song & Zhu, 2018) defined volume refers to the amount of data; variety relates to the structuredness, unstructuredness, or semi-structuredness of the data. (See Table 2.1), and velocity as the speed of data.

Table 2.1: Types of data (Kwon, Lee & Shin 2014)

Types of data	Definition	Examples
Structured	The data can be stored in a relational database.	Select, update, and delete queries that used in SQL
Unstructured	The data that is not classified and filtered	Video, text, and images
Semi-Structured	Semi-structured data that can be found on web pages, e.g., social media	The document is machine-readable because they contain user-data tags.

In contrast to the 3 Vs, other studies (Košcielniak & Puto 2015; Sivarajah et al. 2017; Al Ghamdi & Thomson 2018; Osman 2019; Song & Zhu 2018) added value to claim there are 4 Vs. that characterise big data velocity (speed of data, dynamic data), variety (various forms of data), and volume (a significant amount of data). Then, Song & Zhu (2018) highlighted the five Vs as big data characteristics, putting value at the centre of their discussions. Several academics have agreed that this definition should include the terms volume, velocity, diversity, veracity, and value. (Al-Haj & Khwaldeh, 2017; Oussous et al., 2018; Song & Zhu, 2018; Yang et al., 2017). Nonetheless, Sivarajah et al. (2017)

insinuated 7 Vs: volume, variety, veracity, value, velocity, visualisation, and variability. Thus, visualisation and variability were included in the big data characteristic, as the author believes big data must contain these two dimensions. Furthermore, variability refers to data whose meaning is constantly changing, while visualisation presents the data in a readable manner.

Gupta et al. (2018) presented an extended perspective that merged observation, interpretation, evaluation, and decision (cognitive computing) with the 4 Vs of big data. They merge observation with volume, interpretation with variety, evaluation with velocity, and decision with veracity (Kwon, Lee & Shin 2014). This perspective is plausible as big data needs to be characterised and analysed based on the field of research. For instance, big data in education should be characterised by validating and visualising data towards meeting the contextual needs of a given organisation.

2.3.3. Benefits and Value of Big Data Analytics

Value refers to a continuous belief that a specific mode of existence is socially preferable to alternate modes of conduct or end-states of existence (Korherr & Kanbach 2021). Many academics have discussed the values and advantages of applying BDA in both private and public organisations. – see Table below.

Table 2.2: Big data analytics values

Author	Year	Value creation of big data
(Trieu Van-Hau Thi & Arif 2018)	2018	Effective decision-making; Business intelligence
(Khan, Shakil & Alam 2018)	2018	Improves the teaching process
(Mukthar&Sultan 2017)	2017	Identifying current performance; Developing programs for improving students' performance; Curriculum improvement by providing a new platform for new ways of teaching

(Ashaari et al., 2021)	2021	Improve firm performance in Malaysian higher education
(Rameshwar Dubey et al., 2019)	2019	Improve the trust and collaboration between military and civil firms
(Ghasemaghaei & Calic, 2019)	2019	Data velocity and variety enhance data-driven insight
(Zhu et al., 2019)	2019	Improve the performance of smart transportation systems
(Ji-fan Ren et al., 2017)	2017	Reduces business costs; Kindles business insights; Unravels strategic information; Improves business value and firm performance
(Özemre& Kabadurmus 2020)	2020	Enhances strategic decision making
(Ashaari et al., 2021)	2021	BDA capabilities improve firm performance

Accordingly, studies associate BDA with business performance (Dubey et al. 2019; Maroufkhani et al. 2020) and supply chain logistics (Dubey et al. 2019). Despite the asserted advantages of BDA for decision-making, it remains unclear how BDA influences strategic decision-making processes in the organisation (Janssen, van der Voort & Wahyudi 2017). However, in recent years, big data research in higher education appears to be gaining traction and contributing to improving the sector, specifically in supporting decision-making. Analysing data from multiple platforms and aggregating it could improve decision-making capability while adding other constructs, such as university size and type, would provide further insight to enhance decision-making and predictive analysis (Chaurasia et al., 2018). Furthermore, decision-makers can make better decisions by focusing on student performance and academic achievement (Mago & Khan 2021).

2.3.4. Applications of Big Data Analytics

Technology is growing fast, allowing organisations to gain competitive advantages. One such technology is BDA and its fast diffusion into higher education, health care, finance, business, and private organisations. Effective software tools are needed for BDA; for instance, since 2005, IBM has spent 16 million USD on acquisitions in a big data project (Chen, Mao & Liu 2014). Since then, more tools have been developed and enhanced. According to Ali (2018) and Russom (2011), an enterprise data warehouse (EDW) is among such tools but has failed to satisfy advanced data analytics tasks. They indicated that 64 % of interviewees preferred to perform BDA tasks using EDW. Gupta & George (2016), Dey et al. (2018) identify "NoSQL" databases as tools for storing and retrieving unstructured data. However, Yang et al. (2016) stressed that NoSQL is used for semi-structured data. NoSQL databases includeCassandra, HBase, and MongoDB (Gupta & George 2016; Hassanien & Darwish, 2020).

Recent developments in BDA have introduced new software that includes advanced techniques to ease storing, processing, and visualising big data. One of these techniques is MapReduce. MapReduce is an intriguing approach where data localisation is examined to boost application speed. Hadoop, an open-source version of MapReduce, enables the building of clusters that employ the Hadoop Distributed File System (HDFS) to divide and copy data to nodes where mappers use those nodes. (lia dwi jayanti 2020). Despite the popularity of BDA, its developments are still in the early stages and such development must revolve around organisational needs and goals. Besides, data should be filtered and classified based on the current situation.

2.3.5. Obstacles of Big Data Analytics

Obstacles and challenges always occur at the beginning of any new technology. BDA challenges often relate to data security, data privacy, and technical issues related to data storage and maintenance (lia dwi jayanti 2020). Assunção et al. (2015) claimed that businesses' key challenges are infrastructure for storage, management, interoperability, governance, and big data analysis. In contrast, the research by Adepoju (2020) emphasised that management for BDA is the main problem and presents two main challenges: engineering and semantics. Engineering refers to storing and querying this data in real-time, while semantics refers to the values created by this big data. Similarly, Günther et al. (2017) describe barriers such as limited stakeholder interest, underestimating the development of organisational models, and being limited by a dominant, traditional business model. Big data projects fail due to strong business requirements, workforce planning, technological infrastructure, top-level management participation, and supplier procurements (Gupte 2018).

In the light of BDA in Saudi higher education, prior studies have presented context-oriented observations. For instance, Ahmed (2016) highlights that big data barriers in education are uncountable but will often involve security, privacy, IT infrastructure, and top management support. Mukthar and Sultan (2017) concurred that security, privacy, analytical skills, top management support, and IT infrastructure inhibit BDA in Saudi higher education. The challenges revolve around the actors, as other studies insist that data scientists, ITC support, management support, and strategic planning are higher education's main challenges (Song & Zhu, 2018; Hassanien & Darwish 2020; Williamson, 2018; Minkov et al., 2017; Rakesh et al 2021) .

The lack of management support in BDA in higher education seems apparent. However, clear planning from planning and development teams within universities could make big data development easier. For instance, the planning and development department could create clear, detailed plans for BDA projects, including factors considered to be challenges and how to overcome these challenges to convince top management about the new project. In the next sections, we will discuss the state of BDA in educational systems and Saudi Arabia.

2.3. Big data analytics in Developing Countries

The field of BDA is growing dramatically and has been shown to significantly impact the development of many countries, including developing countries. Using BDA can be a tremendous boon to developing countries by helping governments better understand the needs of their constituents and their ability to respond to those needs by tracking public sentiment through social media. Data analytics services can also help governments make better-informed decisions about allocating resources, such as how much funding to send to a particular area based on the needs of that community. BDA in the developed world is transforming business, government, and healthcare services. With access to a global network of knowledge, companies can no longer claim ignorance regarding how their actions impact the environment and the lives of their customers. At the same time, governments can more effectively monitor the spread of disease and other public health threats and track down frauds and tax evaders by analysing citizen behaviour.

BDA is complex and often confusing, especially in developing countries. It can potentially change entire ecosystems of commerce and industry, but it is not easy for companies to implement, especially in places where many other priorities are competing for resources. Some researchers have suggested that one way BDA could be used in developing countries is through mobile technology. Mobile phones are becoming more ubiquitous even in developing countries and are often used to collect information about people's behaviour and activities. This information could potentially be used for BDA to improve services such as healthcare, banking, transportation, and other areas that can help improve a country's development (Global Pulse, 2021).

Achieving the above services could support the UN's ambitious goal of ending poverty by 2030. But how can we ensure these goals are achievable when so many factors are at play. This is where BDA taking place; it allows developing nations to harness their collective knowledge and expertise in order to achieve better results faster (Guo et al., 2021). Big data analytics may also reduce corruption and promote transparency by decreasing human-introduced mistakes and fostering data journalism in third-world countries. This concept underpins the creation of algorithms that detect and filter biased material in society's digital resources (Wani, 2019). Unfortunately, there are some unique challenges that many developing countries face in their attempts to use BDA.

Accordingly, developing countries do not have the infrastructure to access large amounts of data. In addition, data may be collected in less-than-ideal conditions, which can decrease its quality. The lack of data or the poor data quality can make it more difficult for these countries to develop good models for predictive analytics. Another problem is that many developing countries face is the lack of trained professionals who can work with big data or perform predictive analytics. Such problems make it impossible for developing countries to utilise big data effectively and use BDA techniques.

Taking cloud computing, as an example, it is a relatively new technology that has the potential to significantly improve the health information systems of developing nations (HIS). This new form of HIS may help underdeveloped countries close the digital gap by offering computers as a utility service. Purkayastha and Braa (2013) examine cloud computing models and operational business intelligence tools to see how they can improve decisions in health service supply. According to their research, the digital divide significantly influences the healthcare market. In this perspective, there are two distinct sorts of digital divisions. The first is a proxy for access to internet-connected technologies and their utilisation in various health systems. The second is a disparity in access-to-access technologies.

Big data analytics research is fairly recent, and several unexplored areas exist. One of these domains is 'big data readiness,' or BDRI, which refers to an entity's preparedness and desire to utilise big data, whether a person or a country (Pedro et al., 2019). A country's preparedness is worth investigating before further assessments on BDA adoption and use. Unfortunately, there is a dearth of literature on big data in developing nations. Also, there is no index or methodology for assessing developing nations' readiness to leverage big data. Joubert et al. (2021) propose and discuss an index to quantify this preparedness, which is then applied to all African nations to address the second research question: how do African countries perform in terms of the BDRI? The findings of this study indicate that while most African nations trail behind in preparation for Big Data and AI, these technologies may nevertheless help the reduction of corruption, particularly in countries where corruption is viewed as a big concern.

Perhaps the best example of how big data may be utilised to benefit society is the Engineering Social Systems (ESS) project in Kenya. The project enabled Nairobi government to better allocate resources for infrastructure development and other requirements by using geographical mobile phone transaction data to estimate slum expansion. They have discovered that by analysing large data, they can forecast which places need additional toilets and safe drinking water and which infrastructure would require upgrades (Kshetri, 2015).

2.5. Big Data Analytics in Saudi Context

Big data analytics is a new technology in Saudi Arabia. New technologies are an investment focus for the Saudi Government as they try to maximise the country's income and achieve its vision for 2030. The government implemented four huge databases, including legal entities, population, natural resources, and macroeconomics DBA. These databases enable decision support, information technology, and content services (Liwei & Marketing 2017). The diagram below illustrates the implementation of these four databases within Saudi Arabia national data centre.

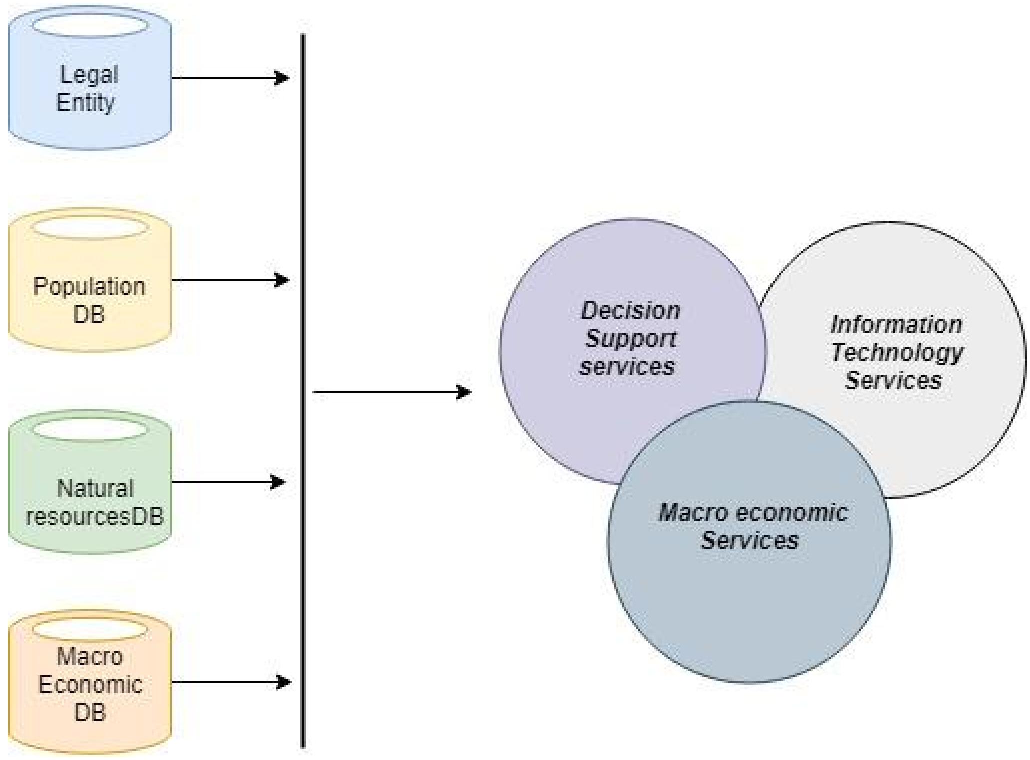

Figure 1: Types of Databases in Saudi National Data Centre Adopted from (CITC 2016)

According to computer weekly (2016), Big data analytics would have been key to the national plan. Consequently, Dell E.M.C. partnered with the nation's top oil producers and government organisations on big data projects. Similarly, Arab News (2018) stated that Saudi Arabia, joined the united nations of BD Global Working Group. The selection of the Kingdom reflects a move towards the strategic restructuring of the Kingdom's analytical industry. The executive branch provides full assistance for its mission in supporting national transformation initiatives. This investment is expected to help the Saudi Government improve its experience with BDA and its potential advantages.

2.5.1. Brief History of Education in Saudi Arabia

In 1957, Saudi Arabia established its first university, King Saud Bin Abdul Aziz University, in Riyadh, the capital city. However, its establishment was relatively delayed compared with neighbouring countries such as Egypt. There have been formal public schools for adolescent women since early 1960s, as stated by Hamdan (2005). In 1970, the government funded over 2,300 educational institutions, training a total of 126,000 students. By 1990s, girls' colleges had been established across the entire Kingdom. In 1975, Ministry of Higher Education was established as the governing authority for Saudi higher education (Saha 2019).

Saudi Arabia's education system ensures its students are technologically proficient and able to contribute to the country's economic and social development. Likewise, in 2015, the Saudi Arabian government combined education and higher education ministries.(Faiz & Al-Mutairi 2015). Realising the significance of higher education, the government of Saudi Arabia established a number of institutions in major cities. Under the leadership of King Abdullah, the number of universities in Saudi Arabia increased to 35, with different compositions in various locations across the country (Ministry of Education 2016).

As of 2019, there were almost seven million undergraduates enrolled in Saudi universities and colleges, up significantly from fewer than 250,000 in 1970.

In fact 3.5 million Saudi students in 2019 were women .Making up approximately half of the student population. Women attend every single major university as well as a wide variety of all-female and all-private universities. King Abdulaziz University in Jeddah, the most prestigious institution in the Kingdom, opened and began classes in 1968 with just 98 students, 68 male and 30 57 female. Despite the increasing number of Saudi universities, they have not matched the growing population. Saudi Arabian candidates that enrolled in international universities are among the highest in any country. About five percent of Saudi Arabian students pursuing higher education were granted approval and funding to study abroad in 2017. A monthly allowance is provided to eligible students to help with costs including rent, food, and tuition.The Saudi government has collaborated with leading U.S. institutions to fund research in the education field to demonstrate the significance of this scholarship programme. Saudi Arabia's Ministry of Education claimed that in 2019, approximately 93,000 Saudi Arabian students were enrolled in postsecondary institutions abroad.

2.5.2. Big Data Analytics in Education Environment

BDA is considered a new technology in Saudi Arabia, especially in education. There is a lack of research on BDA in Saudi higher education. However, a few Saudi scholars have investigated BDA in Saudi higher education, and their findings are worth exploring. While some focus on BDA infrastructural capabilities, others discuss the application, benefits and challenges. Ahmed (2016) investigated the implementation of BDA in Saudi higher education and noted several factors affecting BDA in Saudi Arabia. Such factors include data security, pprivacy, analytical capabilities, IT infrastructures, the support of senior executives, and collaborative data initiatives. Alhamed (2017) comprehensively discusses BD, learning analytics, Natural Language Processing and it impact on making decisions. It also provides a comprehensive learning analytics solution based on a distributed system that assists academic supervisors and consultants in institutions in making decisions about individual students.

Similarly, Mukthar and Sultan (2017) examined the same phenomenon with a focus on concepts, basic definitions, possible applications, and concerns about its implementation and growth. They delved into the benefits of BDA in the educational system. They reported benefits such as improving students' performance, providing a new platform for learning, introducing new teaching modes, and promoting research collaborations. They suggested that BDA in Saudi higher education requires policy and role definition, such as, who is responsible for storing, analysing, and updating big data and improving data privacy. In addition, Baig and Jabeen (2016) indicated the role of BDA in predicting student behaviour that may lead to terrorism.

In the US, universities have applied BDA to support student admission processes, allocate campus resources and attract more funding through donations (Attaran, Stark & Stotler 2018). Bian & Wang (2021) investigated the impact of BDA on the management of Chinese Colleges and Universities CAU; they summarised that BDA could reverse the shortcoming of the traditional management methods and contribute to improved institutional management. Ong (2016) conducted a study on the rewards that BDA could bring to the higher education sector in the UK. They stated that BDA would enhance the education quality and good staff and student experience. Undoubtedly, BDA in Saudi higher education is still in its early phases (Sultan, 2017); therefore, more work remains to be done before the promised benefit of BDA can be realised. Even though BDA is still in its infancy, Fujimaki & Morinaga (2012) argue that Saudi Arabia has the potential to collect and retain data from diverse and varied sources, which could aid in the performance by eliminating redundant data.

2.5.3. Big Data Analytics & Improving Decision Making

Although the rising interest in BDA in Higher Education Institutions (HEIs), research on BDA capabilities at HEIs is sparse. Understanding the factors that enable data-driven decisions is critical (Shamim et al., 2020) – specifically, we must understand how to manage data as an enabler of decisions (Provost & Fawcett 2013). An in-depth analysis revealed that BDA could enhance the performance of organisations and turn HEIs into data-driven organisations and value creators (Chaurasia et al. 2018). With BDA, HEIs can improve productivity and profitability by enhancing organisational learning, decision-making and new products and services (Inkinen, Kianto & Vanhala 2015). Decision-makers can make more informed decisions (Moreno et al., 2019) as BDA adds value to the decision-making process (Sekli & De La Vega, 2021). Janssen, van der Voort & Wahyudi (2017) explain that firms make better decisions when data is fully comprehended and integrated with other data into a big data chain. However, Shrestha, Ben-Menahem & von Krogh (2019) cautioned that incorporating algorithms in decision-making could affect strategic managers' responsibility, motivation, and performance.

Equally important, BDA plays a crucial role in improving organisational decisions; but collecting and analysing reliable or high-quality data is vital to strategic decisions and has been associated with high-quality decisions (Intezari & Gressel 2017; Ghasemaghaei & Calic 2019). Nevertheless, data quality is challenging in adopting BDA in all domains, and many questions have been raised, does it help make better decisions? Does it enhance competitive advantage? If the answers are affirmative, one may conclude that their data is of high quality, which enhances the preciousness of strategic decisions – with cases observed in the education sector (Inkinen, Kianto & Vanhala 2015). However, the decision-making quality may be influenced by other factors beyond data quality and BDA capabilities (Janssen, van der Voort & Wahyudi 2017). Such factors may include contracting and transactional administration with providers of big data, the collaboration between decision makers, and big data analysts, and process integration and standardisation (Janssen, van der Voort & Wahyudi 2017).

Mahroeian & Daniel (2021) questioned whether the educational system in New Zealand is ready to employ BDA in improving strategic decision-making. They conclude that employing such a technique will improve the monitoring of the educational process rather than improving the quality of learning, teaching, and strategic initiatives. Big Data allows decision-makers to identify, comprehend, examine, and forecast learners' behaviours, the progress of educators, the course results, and other institutional functions. Alammari (2020) studied the benefits of BDA in three Saudi universities and found that decision-makers were more likely to make critical decisions based on the insights generated.

With technologies related to BDA, i.e., Hadoop and Natural Language Processing, huge data can be processed and analysed; however, such amounts of data can be collected and analysed when the appropriate tools are selected (Boncia et al. 2017). Merging analytical tools with process management and all required data is pivotal for better decision-making and can profoundly impact corporate strategy (Osuszek, Stanek & Twardowski 2016). Big data can affect all strategic, tactical, and operational decisions. The concern is executing specific tasks reflecting the tactical decisions (Ranjan & Janardhanan 2020). Consequently, many firms depend heavily on data to make strategic and operational plans and actions (Almutairi 2021). According to Cervone (2016), organisations' main challenge in adopting big data is where to start implementing BDA. Nonetheless, thanks to BDA, the increased efficiency and effectiveness in an organisation's decision-making is indisputable (Chen 2019; Baesens, De Winne & Sels 2017).

2.6. A Social-Technical Approach to BDA

While all definitions, technologies, and benefits surrounding big data are elucidated, there is a lack of consolidated discussion recognising the multivariate perspective on big data analytics, particularly, where is the social in big data and analytics technology? Despite the many studies investigating big data and BDA, there is little discussion on the social-technical realm of big data technology. Socio-technical systems are omnipresent in all technology applications as technologies are designed, used, and governed by people. Through the social-technical perspective, we evaluate the interaction between the technical factors (technology and tasks) and the social factors (actors and structures)

(Bostrom & Heinen, 1977). Dremel et al. (2017) apply the STS perspective to BDA to argue that it involves multiple task possibilities, technology implementation, and development of people capabilities, a data-driven organisational culture, and organisational structures that ensure interdepartmental collaboration. This study articulates the STS in BDA by uniting both views.

2.6.1. Social Subsystem

The social system refers to the structures and actors in BDA systems. In other words, it constitutes organisational structures and the people handling the technology (Cronemberger, 2018). The BDA social subsystem will consist of social factors, including BDA performers and big data-oriented organisational culture.

2.6.1.1. Big Data Analytic Performers

People are central to BDA systems because they are responsible for turning the data into insights by aligning the analytics to organisational processes, procedures, and goals (Fernando & Engel 2018). Previous studies (Hargiss & Member, (2017) have emphasised the importance of human factors in implementing new systems. Others (Dremel et al., 2018; Davenport, Barth & Bean, 2012) highlight the IT workforce as a key player in performing BDA tasks. In the case of HEIs, BDA workers are considered academic and non-academic IT professionals who are accountable for big data security and privacy, and quality. This workforce may have low technical skills but other human capabilities that augment the use of BDA, such as culture and governance, strategic planning, and management, including leadership, coordination, and control (Korherr & Kanbach, 2021).

Data scientists play a crucial role in producing high-quality data for effective decision-making. Data quality analysts conduct data quality evaluations by evaluating and interpreting various data quality parameters. (Christopher Tozzi, 2021). In addition, the role of data scientists in improving the accuracy of data collected from machine learning and other automatic processes is becoming increasingly important. Unstructured data is a major problem that includes data that has been duplicated or entered incorrectly, is incomplete, is formatted inconsistently, or lacks context to be understood correctly (for example, a list of state abbreviations without a key explaining each abbreviation).

Data scientists identify how data is used in a company and how accurate it needs to be. They analyse raw data and help determine the best ways to clean, transform, and present it (Rakesh et al 2021). They also test the accuracy of data as used by different functions within an organisation to find inaccuracies or biases. Often, this means finding and eliminating duplicates, correcting errors, and ensuring that all information is up-to-date and relevant. For example, dates may be entered as "11/13/2019" or "November 13th, 2019" across different datasets. If there are inconsistencies between datasets, it complicates the data scientist's ability to merge them (and if they cannot merge them, they cannot analyse them).

Data scientists are responsible for creating algorithms that can effectively analyse large amounts of data and apply those analysed data to solve real-world problems. The goal is to make accurate predictions relying on the data that was stored from various sources. In addition, they can improve the accuracy of data by improving tracking methods and algorithms. This means that more accurate numbers would be available for decision-making, leading to better overall decisions (Taleb et al., 2021). Data scientists also perform data profiling, defining the relationships between variables and entities in a dataset and identifying patterns and trends (Chen et al., 2020). Data profiling generally produces statistics such as null value percentages, min and max values, average values, and counts for categorical variables. Data profiling helps them identify trends and anomalies in the dataset that can be used to make decisions or predict business outcomes. However, when reviewing these statistics, the analyst must consider the dataset's context and the purpose of their analysis.

As discussed earlier, data scientists are also charged with taking large amounts of information and turning it into something valuable. However, one significant challenge data scientist's face is dealing with disparate datasets that do not conform to a common format. One way to solve this problem is by using geocoding. Geocoding takes addresses from different countries and converts them into latitude/longitude coordinates so that all addresses can be plotted on a map together (Yao et al., 2019). For example, for an address in New York City (NYC) to plot correctly on Google Maps with other addresses worldwide, NYC needs its unique mapping system where all streets are allocated latitude/longitude coordinates. Geocoding is an example of standardisation that data scientists do that involves assigning geographic coordinates (latitude and longitude) to locations provided in different formats (AIHA, 2022). For example, a location might be recorded as “100 Main Street, Anytown, NY,” or simply “100 Main Street,” or even just “Anytown.” A data scientist would need to convert these addresses into latitude and longitude coordinates before they can be used in maps.

2.6.1.2. Big Data Organisational Culture

Organisational culture (OC) denotes organisational structures which involve systems of communication authority and workflow (Leavitt, 1965) cited by (Dremel et al., 2017). The term organisational culture refers to the pattern of an organisation’s reaction to the opportunities and challenges it faces (Westrum 2004). Westrum noted that another way to see culture is to consider the collection of procedures that determine an organisation’s approach to the problems it faces. Organisational factors have been recognised as playing a role in the communication processes (Westrum 2004), information security (Al-umaran 2015), and the adoption of information systems (Bayomy et al., 2021). Whether organisation culture positively or negatively influences BDA and decision-making appears to relate strongly to data and information management, among other activities.

Organisational culture is critical in developing new systems and implementing creative and innovative technologies (Frisk & Bannister 2017). In the context of information systems, organisational culture in countries such as Saudi Arabia is often associated with national culture, organisational leadership, interpersonal trust and interaction, and the organisation’s technological orientation. These dimensions of organisational culture were found to influence attitudes and behaviours towards information security (Basfar & Bajunaied, 2020). Organisational culture is critical to adopting and managing information systems in North Africa and the Arab Gulf Region irrespective of the underlying cultural values, such as adhocracy or hierarchical values (Rawashdeh, Al-Saraireh & Obeidat 2015).

BDA is an innovative approach, but its adoption and implementation could be influenced by organisational culture and leadership (Fernando & Engel 2018). A prior study has argued for exploring the role of a data-driven culture and noted that this culture might often drive BDA performance and outcomes. However, organisational culture and BDA are still overlooked in Saudi higher education (Thirathon, Wieder, Matolcsy, & Ossimitz, 2017). Two important factors represent a data-oriented organisational culture; (1) responsiveness to accepting new BDA technological improvements and (2) ability to adapt to emerging technological improvements. It is important to note that emerging technological improvements are often associated with enhancing big data security and quality (Ardagna et al., 2018).

2.6.2. Technical Subsystem

The technical subsystem constitutes the technologies and tasks required to achieve a desired goal or output (Bostrom & Heinen, 1977). The technical realm is often considered a key aspect of successful information systems (Cronemberger, 2018). To build a general view of the BDA technical system, we can assume Delone and Mclean's perspectives on IS success. In a big data environment, we look at BDA technological improvements as a key aspect of the technical system, and such technological improvements often revolve around system quality. Previous studies examined system quality as user-friendliness, ease of use, easy to adapt, easy to access, response time, and privacy (Ji-fan Ren et al. 2017). Concerning the big data case, the key measures of quality widely noted in literature revolve around big data security (Abouelmehdi et al., 2017; Mancini, 2017; Lombardo, 2018) and big data quality (Ardagna et al., 2018). System quality at large will influence the net benefits of the system (SF Alsahli 2018). Existing studies on system quality and BDA show that system quality is a critical success factor in firm performance (Ardagna et al., 2018).

2.6.2.1. Big Data Security

While big data analytics has ignited opportunities for many sectors, ensuring security and privacy is central to creating big data value. Implementing big data security is a daunting activity worsened by the growing complexity of effective methods and procedures (Khaloufi et al., 2018). Big data security revolves around four areas: data privacy, management security, infrastructure security, and reactive security (Jung 2017). More specifically, the organisation must focus on Hadoop security, cloud security, key management, anonymisation, monitoring, and auditing (Conti et al., 2017). Data perturbation, encryption, and anonymisation are critical to preserving privacy (Fang et al., 2017). For example, technologies for authentication, encryption, data masking, and access control are anticipated to secure patients' personal and healthcare data (Chan

2015). Also, policies and regulations, transparency, and consistency are called for to reinforce big data security (Alalawneh & Alkhatib, 2020; Abouelmehdi et al., 2017)

Security concerns have greatly increased with technological advances; therefore, data security is often integrated into the entire life cycle from collection, storage, analytics, and utilisation and destruction (Koo et al., 2020). Data should be protected from the beginning, as it is being gathered, to the end, when it is being analysed, and decisions are being made (Venkatraman et al., 2019). However, big data security cannot simply be bolted onto a system that does not have the required capabilities. Koo et al. (2020) defined a framework for ensuring security and confidentiality throughout the lifecycle of large data. During collection, firms must enforce a privacy policy and apply privacy-preserving technologies, including access control and homomorphic encryption. At the storage phase, firms must consider audit trails and enforce attribute and identity-based encryption. The analytics and utilisation phases must be guided by privacy-preserving data mining and publishing. Lastly, the destruction phase must involve degaussing and overwriting.

Breaches can happen for many reasons, and one way to avoid this is by taking advantage of data security software that can help prevent breaches from occurring in the first place (Moorthy et al., 2015). Companies are forced to consider costly techniques to monitor data accessed and ensure authorised access across distributed locations. Decision-makers look beyond traditional business models to find solutions (Tian, 2017). One such solution is ensuring big data security in decision-making processes. For companies to use big data securely, it is important to ensure that the information collected is secure, which implies not only protecting the servers where this information is stored but also ensuring a non-violation of privacy. The question of improving decision-making and preventing decisions from going awry persists as security concerns rise. Presenting theories is one thing, and influencing practice is a different story (Tan et al., 2017).

2.6.2.2. Big Data Privacy

Privacy-preserving is the major tension in big data (Fang et al., 2017). Privacy is often defined differently among scholars informed by culture, religion, and laws. Fang et al. (2017) reviewed several definitions and concluded that privacy is “The ability to be free of covert monitoring and to decide when, how, and to whom one's personally identifiable information is disclosed. (p. 547). Tran and Hu (2019) defined privacy as the practice of not disclosing confidential information regarding people or organisations. Confidential information is sometimes used interchangeably with data privacy but distinct from a security perspective. Privacy of big data is a "data-oriented" concept concerned with the data itself and the goal of restricting access to the data to authorised parties. It is possible to attain maximum privacy by not sharing any data in any way. Disclosing too much aggregate data may jeopardise user privacy. However, the insights generated must be accurate for data to be valuable in an analysis. Unfortunately, maintaining a transaction between privacy and precision is challenging with privacy-preserving data analysis (Rebello & Tavares, 2018; Fang et al., 2017).

Organisations continuously collect data for product development and better decisions (Jain et al., 2016). For example, Walmart collects billions of data points from its customers to better understand their shopping patterns, which helps them stock products accordingly. As more and more data is collected, users are growing increasingly concerned about their privacy. Organisations must recognise these concerns and align their practices to privacy legislation. For instance, the European Union requires explicit consent to collect personal information. Such legislations continue to challenge companies like Facebook, which require users to agree with the terms of service before accessing their social media accounts (Hervais Simo, 2015). Data privacy is a huge issue for businesses and individuals alike. With the ability to collect data about anyone at any time, it could be difficult to determine when and where one crosses the line into unethical practice. Therefore, the collected data must be analysed correctly not to violate anyone's privacy. Organisations need to develop policies that ensure the responsible use of consumer data. They can do this by defining their information need, avoiding collecting more data than needed, and implementing a plan on how they will use it. Unfortunately, political affiliation and religious beliefs could influence organisational data collection practices.

Privacy issues are often highlighted when regulators, consumers, and companies discuss using big data. The issues raised can be categorised into four: informational, physical, decisional, and dispositional (restriction on attempting to read one's state of mind) (Fang et al., 2017). Such privacy concerns can be ensured in three ways (Kshetri, 2014):

building and maintaining a strong privacy culture, implementing conformance processes to ensure that the organisation adheres to its privacy commitments, and establishing a comprehensive set of privacy policies. Training is perhaps crucial to creating and maintaining a healthy privacy culture. It is important for employees to understand the organisation's commitment to privacy and what it means for their work (Schwieger, 2016). For example, if you are handling a customer's personal information, you need to know why you are doing so, what the customer expects from you, how they expect data will be used and shared, and what the consequences are if something goes wrong.

This approach has implications for both large and small businesses and startups, which may be looking for ways to utilise their data and maintain privacy simultaneously (Muhammad Asif Qureshi, 2020). Perhaps a decision-making culture based on trust and openness could be considered. When managers trust each other and their company's values, it could be easier for many to make ethical decisions in the face of conflicting imperatives. In the era of BD, an enormous amount of data is being collected in a variety of data formats. This data might be sensitive or personal and most likely will be shared with others. Such issues have raised the significance of a system that ensures big data privacy, specifically when it comes to improving the privacy of decisions made by top management in Saudi Arabian higher education.

2.6.2.3. Big Data Quality

Big data quality relates to providing the correct data at the proper timing to the proper people. Data quality is multi-dimensional and can be assessed for intrinsic quality, such as its accuracy and structure, or contextual quality, such as its completeness, consistency, and timeliness (Loshin, 2011). Intrinsic quality relates to the data values, while contextual quality relates to the validity of the data in relation to other data elements or records (Loshin, 2011). In the light of BD, other quality dimensions, including trustworthiness, must be considered (Ardagna et al., 2018). Trustworthiness refers to the probability that the value of a data item is correct (Ardagna et al., 2018). Accuracy relates to the adherence of data to user interests, while completeness refers to the quality of representing all but only that which meets the user's needs (Batini et al., 2015). Consistency relates to the capability of data to comply with business rules and formalisms (Batini et al., 2015). In addition, big data quality depends on the data source, type, and application (Batini et al., 2015). The ability of the firm to maintain data quality and its experience using external sources influences its ability to adopt BDA (Kwon et al., 2014). Maintaining big data quality calls attention to the organisation's big data security and privacy frameworks, techniques, policies, and procedures.

BDA system must support several quality dimensions to enhance organisational performance (Fernando and Engel 2018). The ability to work with large amounts of data from diverse sources allows for better decisions, but the quality of the data matters. For instance, by analysing social media trends, businesses can track how consumers perceive their brand—and use that information to improve their marketing strategies and products (Abkenar et al., 2021). Similarly, businesses can use big data analytics to anticipate better and meet consumer demand, which helps them achieve greater cost efficiencies and profitability. Good data quality improves not only decisions but also the efficiency and effectiveness of operations (Weigel & Wihbey, 2013). With good data quality comes the ability to assess performance in real time and identify areas where process and product improvement is needed. This kind of self-awareness can foster better and faster solutions (Wright et al., 2019).

Equally important, private and public sectors struggle with poor-quality big data (Trieu Van-Hau Thi, Cockcroft, and Perdana, 2018). Many issues can cause data quality problems. In some cases, data quality problems arise due to errors in the data collection process. For example, suppose a customer service representative incorrectly enters a customer's phone number into a database while updating the customer's account details. In that case, bad data will continue propagating throughout the organisation until someone catches the error. In other cases, data quality problems are caused by changes in business requirements over time (Singh, 2019). To gain business value from BDA, organisations should maintain good quality data, particularly by striving for an optimal alignment of big data technologies and their strategic decisions (Fosso Wamba, Akter & de Bourmont 2018). Data quality assessment is critical as it supports identifying and analysing pertinent data for valuable results.

2.6.2.4. Big Data Tasks

Big data tasks are pivotal to the technical subsystem, which revolve around the big data lifecycle i.e., storing, analysing and visualising big data for enhancing the decision-making. According to Koo et al. (2020), there are five stages: collection, storage, analytics, utilisation, and destruction. Alshboul et al. (2015) reduce the stages to four, including collection, storage, analytics, and knowledge creation. On the other hand, Gerber (2018) argues that core tasks revolving around the storage of massive data from several reliable sources, analysing it, and visualising it in a usable way. Looking at Gerber's argument, storage relates to how various data types collected from many sources and stored in various formats. Data aggregation, replication, and storage are required to complete the storage phase of managing big data. (Siddiqa et al., 2016). The big data context raises more demands for distributed storage and security (Koo et al., 2020).

Data analysis involves the application of different types of analytics, including data mining and algorithmic approaches. The attention is on the issue and its appropriate solutions, a choice to be taken, and numerous interpretations analysed from the data. The organisation must integrate its strategy with big data to create data-driven value. (Bishop 2019). A major concern, however, is that "In data analytics, the effectiveness of privacy protection is inversely related to data processing, i.e. it is challenging to improve processing performance while preserving sensitive data." (Koo et al., 2020, p. 6).

Another key stage in the data lifecycle is data visualisation, which other studies denote as utilisation. While data may be quickly collected and stored, generating insights and understanding it remains challenging (Cheshire & Batty, 2012). As data grows in volume and variety, so does the need for ways to visualise it efficiently and effectively for easy consumption by decision-makers. Organisations strive to generate new information and insights, and data visualisation is critical to enhancing decision effectiveness. Data visualisation can greatly influence decision processes; top management value analytics and apply it to promote their decisions (Thirathon et al., 2017).

Data visualisation is the "representation of data in a visual and interactive format. It gives users conventional ways to view and analyse data dynamically, successfully uncover intriguing patterns, derive relationships and causalities, and enhance sense-making activities." (Bikakis, 2018, p. 1). With the growth of big data, organisations have adopted visualisation tools such as Tableau and Power BI to make data comprehensible. Also, there are growing demands for visual analytics, which provide the capability to analyse data faster, more interactively and intuitively (Lowe & Matthee, 2020). Visualisation demand is associated with improving comprehension (Lowe & Matthee, 2020). Reported visualisation tasks include dimensionality reduction, interactivity, scalability and readability, fast retrieval, data reduction, hierarchical exploration, incremental and adaptive processing, and user assistance (Bikakis, 2018; Lowe & Matthee, 2020).

2.7. Improving Decision-Making

The explosion of digital data has led to a growth in the number of organizations that are turning to big data analytics in order to get insights that will assist them in enhancing their operations, making better decisions, and boosting their profitability.

Analytics performed on large amounts of data have the potential to provide a more all-encompassing picture of a certain issue or circumstance. Large volumes of data gleaned from a variety of sources may help businesses get a more comprehensive knowledge of their customers, markets, and operations, which in turn can contribute to more informed decision-making. Additionally, big data analytics can help organisations identify patterns and trends that may not be immediately apparent, providing valuable insights that can help drive decision-making (Aversa et al., 2018).

Analytics performed on large amounts of data also have the potential to enhance the effectiveness and velocity of processes through which decisions are made. Organisations are able to make choices more rapidly and with a higher degree of precision if they automate the process of data analysis and provide insights in real time (Elgendy et al., 2021) . This can be particularly beneficial in fast-paced industries, such as finance and retail, where rapid decision-making is essential to success.

It may improve decision-making accuracy and reliability. Companies are able to discover and eliminate biases or mistakes that may have influenced prior judgments by analysing huge volumes of data. This allows for the organisations to improve upon past outcomes (Niebel et al., 2018). The analysis of large amounts of data may also assist businesses in gaining a deeper comprehension of the dangers and ambiguities that are connected to the many decisions they face, so empowering them to make choices that are both educated and well-informed.

However, there are also some potential challenges and limitations to using big data analytics for decision-making. One potential issue is the potential for bias in the data itself, which can impact the accuracy and reliability of the insights generated (Mahmood et al., 2022). Additionally, organisations must also be mindful of data privacy and security concerns, particularly when analysing sensitive or personal information.

In spite of these possible obstacles, “big data analytics in the process of decision-making” is expanding at a fast rate, and a lot of studies are addressing the potential advantages and constraints of this approach. Numerous studies show it may improve decision-making accuracy and reliability, especially in sectors such as the retail, healthcare, and financial industries. For instance, research conducted by Hasan and colleagues (2022) discovered that big data analytics may assist financial organisations in improving the accuracy of credit risk assessment, which in turn leads to more educated and lucrative loan choices being made. Moreover, Big data analytics may help healthcare businesses enhance diagnostic and treatment suggestions, improving patient outcomes. (Roden et al., 2017) .

According to the findings of a research conducted by Elgendy et al. (2021), big data analytics may assist retail firms in making inventory management choices that are both more accurate and more timely, which can result in decreased expenses and greater revenues. In addition, research conducted by Xu and colleagues (2022) discovered that big data analytics may assist logistics organisations in improving the effectiveness of their supply chain operations, which in turn leads to decreased costs and higher levels of customer satisfaction.

In general, the evidence shows that it may improve decision-making across several corporate sectors, according to the findings. By providing a more comprehensive view of a given situation, identifying patterns and trends, and improving the accuracy and reliability of decision-making processes, it can help organisations make more informed and profitable decisions.

2.8. BDA and Enhancing Organisanal Perfroamnce

In recent years, corporations have begun to notice the potential for big data analytics to enhance performance, which has led to an increase in the amount of interest around this issue.

The analysis of large amounts of data helps businesses to make choices that are better informed. When businesses examine substantial volumes of data, they are able to see patterns and trends that may not be readily visible when looking at smaller data sets.This can help organisations to better understand their customers, markets, and operations and to make more informed decisions about how to allocate resources and achieve their goals (Hassan, 2019). For example, a retail company might use big data analytics to identify the most popular products, the most profitable stores, or the most effective marketing campaigns.

The analysis of large amounts of data may be used to assist businesses in identifying areas of waste and inefficiency, which can result in financial savings. One research concluded, for instance, that its application in the healthcare may assist discover and reduce needless tests and procedures, resulting to cost savings not just for patients but also for the healthcare system as a whole. Another study found that organisations using big data analytics had a competitive advantage over those that did not, with improved efficiency and decision making leading to higher profits (Gomes et al., 2022).

The potential to enhance both the customer experience and the customer's loyalty is another advantage of using big data analytics. It is possible for businesses to get an understanding of the requirements and preferences of their consumers, allowing them to better cater their goods, services, and communications to these requirements. For example, a financial institution might use big data analytics to identify the most profitable customers, and offer them personalised products and services to encourage loyalty (Schneider & Seelmeyer, 2019).

However, implementing big data analytics also presents some challenges. One of the biggest challenges is the need for skilled personnel to manage and analyse the data. This requires organisations to invest in training and development for their employees, or to hire specialised consultants or data scientists. Another challenge is the need for robust IT infrastructure to support the storage and processing of large amounts of data (Aversa et al., 2018). This can be expensive and may require significant investments in hardware and software.

In addition to these technical challenges, there are also cultural and organisational challenges to consider. Big data analytics may need fundamental alterations to the way an organisation does its day-to-day tasks. Employees who are used to doing their jobs in a certain manner may object to the introduction of these alterations. Businesses must convey its benefits to employees and include them in the planning and execution phase of the initiative in order for the business to be successful in overcoming these hurdles (Khan, 2021).

Several factors may affect how successfully big data analytics improves corporate performance. The accuracy of the data is among the most crucial considerations to take into account. Data that is inaccurate, incomplete, or out of date may lead to conclusions that are incorrect and judgments that are unsuccessful. It is therefore important for organisations to ensure that their data is accurate and up-to-date, and to invest in tools and processes to improve data quality (Shereni & Chambwe, 2019).

Another important factor is the ability to extract meaningful insights from the data. This requires the use of advanced analytical techniques, such as machine learning, artificial intelligence, and predictive analytics. These tools assist firms detect data patterns that human analysts may miss (Lv et al., 2021). Effective implementation requires specific skills and knowledge.

Third, company culture and leadership might affect big data analytics. Organisations that are open to change and innovation, and that have leaders who are supportive of data-driven decision making, are more likely to successfully implement big data analytics (Ogbuke et al., 2020).

It can also help organisations to optimise their operations and improve efficiency. By analysing data from various sources, organisations can identify bottlenecks, inefficiencies, and waste in their processes, and implement changes to streamline their operations (Maheshwari et al., 2020). For example, a manufacturing company might use big data analytics to identify the most efficient production methods, or a logistics company might use it to optimise routes and reduce fuel consumption.

Several studies suggest big data analytics may boost organisational performance. It may improve the accuracy and speed of decisions, enhancing consumer pleasure and loyalty (Kamble et al., 2018). Big data analytics may help firms uncover new business possibilities and better understand consumer wants, leading to greater market share and income, according to Oyewo et al.

In conclusion, big data analytics has the potential to enhance organisational performance in a number of ways, including by enabling more informed decision making, optimising operations, and improving customer experience.

Table 2.3 summarise how the current study draws on the mentioned literature to explore and suggest factors that build support for BDA in Saudi higher education.

Table 2.3: Summary of literature and way forward for the present study

Author	purpose	Methods	Key Findings
(Dubey et al., 2019)	Investigate the impact of BDA in improving the culture of civil and military organisations	Theory: (OIPT)	BDA has a significant impact on swift trust and collaborative performance. Flexible orientation has positive effects on path BDA
		Region: various countries	
		Sample No: 373 organisations	
(Côrte-Real et al., 2019)	Examine the influence of BDA on an organisation's performance	Theory: Delphi study	The model explains 62% of BDA and its influence on performance.
		Region: Europe	
		Sample No: 173 firms	
		Region: Greek	
		Sample No: 175 IT managers.	
(Aljumah et al., 2021)	BDA dynamic cababilities on firm performance and business values	Theory dynamic capability view	The study indicated that there is a positive impact of system and information quality on improving the firm performance.
		Region: UAE	
		Sample No: 295	
(Müller, Fay & vom Brocke 2018)	BDA and its effect on firm performance economic perspective.	Theory: ----------	BDA assists in improving business performance. IT that enables BDA to help to improve firm productivity.
		Region:----------	
		Sample No: 814 firms	
(Sherzod & Liu 2019.)	BDA influencing decision making and organisational performance	Theory: Simon's decision making	BDA impacts the effectiveness of enterprises, small and medium ones
		Region: Uzbekistan	
		Sample No: 221	
(Shamim, Zeng, Khan & Zia 2020)	BDA and its influence on decision-making performance in governmental firms, as well as knowledge capabilities	Theory----	BDA mediates the knowledge and social capital. It impacts both knowledge capabilities and social capital within the firm
		Region: China	
		Sample No: 108	
(Adrian et al., 2018)		Theory: -------	

	Big data analytics quality, implementation assessments technology, organisational and technological aspects (long term)	Region: Malaysia Sample No:142	BDA implementation assessments have a relationship with decision-making effectiveness
(Frisk & Bannister 2017)	The impact of top management culture on BDA and its advantages on improving decision making	Theory: action research design (Noval) Region: Sweden Sample No: three organisations	Adopting such an approach improves the decision-making culture and enhances the firm's cooperation.
(Popovič et al., 2018)	How BDA impact operational management in manufacturing industry	Theory: IT business& Resource-based view Region:---------- Sample No: Three companies	The findings show that data source, accessibility, types, and organisational readiness facilitate the improvements of DM
(Mcconnaughey & Member 2020)	Factors influencing BDA decision making after adopting BD (social and organisational aspects)	Theory: technology-organisation - environment Region: United states Sample No: Three firms	The study found that the most significant factors toward improve decision-making are organisational, environmental, and technological.
(Rialti et al., 2019)	BDA capabilities on, i.e., IT infrastructure, top management skills, and its impact on firm performance.	Theory: BDA capabilities Region: Europe Sample No: 259 managers	The findings stated an impact of BDA capabilities on firm disingenuousness and agilities.
(Trieu Van-Hau Thi & Arif 2018)	The impact of using Business Intelligent systems on increasing the decision-making effectiveness.	Theory: BI and BI use Region: United States Sample No: 400 BI users	The study found that BI has a significant influence of the effectiveness of decision making.
(West et al., 2018)	The study compares the experience of learning analytics among Australian and Malaysian academics.	Theory: ----- Region: Australia/ Malaysia Sample No: 577 academics	There is a need in understanding educational policies, culture in applying learning analytics
(Sinha 2020)	BDA in Indian higher education, challenges, applications, and significance of BDA to improve the education sectors in India	Theory: LR Region: India	

		Sample No:-------	BDA Could enhance the performance of Indian higher education by using the newest technology.
(Alhamed 2017)	The advantages of BDA and NLP in the educational sectors	Theory: LR Region: Saudi Arabia Sample No:--------	BDA and NLP could provide effective tools for determining student retention. The study Indicated that such tools could assist the decision-makers in identifying the reasons behind student retention.
(Attaran, Stark & Stotler, 2018)	The opportunities and challenges of BDA in US higher education	Theory: LR Region: US Sample No:--------	The researcher stated that big data applications that can assist academics and administrators in making better decisions
(Shorfuzzaman et al., 2019)	BDA toward mobile learning analytics, learners' readiness, factors driving from mobile learning analytics in higher education	Theory: TAM3 Region: Saudi Arabia Sample No: 140	BDA has a significant impact on supporting mobile learning analytics in higher education. The study also found family support and financial factor has an impact on adopting this new technology
(Aljahdali & Al-ghamdi 2020)	Investigates the significance of BDA in the university network	Theory: Various Theories Region: Saudi Arabia Sample No: 125 students	Network performance has a direct impact on operational and dynamic capabilities
(Ashaari et al. 2021)	Explores the capabilities of BDA in enhancing decision-making (data-driven), which improves the performance of higher education institutions.	Theory:Resource-based view& information procession theory Region: Malaysian higher education Sample No:	The connection between BDA skills and enhanced decision making as well as data-driven decision, plays critical roles in enhancing the performance of higher education in Malaysia

2.7 Chapter Summary

The literature review explored the boundaries of BDA by delving into the definitions, the application in less popular contexts such as HEIs and developing countries and discerning the social and technical realms. Existing studies have reported the technical and organisational barriers to adopt BDA (Günther et al. (2017). Specifically, Lunde, Sjusdal & Pappas (2019) and Raut et al. (2021) discovered that the most difficult obstacles to overcome when implementing analytics are not technological but managerial and cultural. With that, the literature review sought to develop an STS perspective on BDA and show how the social and technical aspects interrelate to influence data-driven decision-making.

Chapter 3

Theoretical Background and Research Framework

3.1. Introduction

Chapter two discussed existing evidence on BDA and introduced the social and technical facets of BDA for strategic decision-making. This chapter discusses information system theories that underpin the sociotechnical view of work systems and the application of BDA in organisational processes and decision-making. In this chapter, we revisit prominent theories, including the theory of reasoned action, the theory of planned behaviour, the technology acceptance model, and it's following contextualised advancements, – including TAM2 and TAM3. With earlier models reviewed, we later focused on and discussed the social-technical theory (STS) and its fitness to this investigation as opposed to prior theories. Uniting the STS and DeLone and McLean theory, we discuss the research framework applied in this study and proposed hypotheses. Finally, the chapter concludes with a summary.

3.2. Information System Theories Relevant to This Study

Incorporating social and technical factors into the design and development of scientific research is crucial since they allow a researcher to draw their investigation on more than a single theory, allowing the scholar to view the phenomena being investigated from different angle. Such integration is even more required in the era of rapid technological advancements. In the case of big data, previous studies focused on the technological realm and neglected the significance of the social aspects (Ashaari et al., 2021). Considering the social and technical factors generates a broader understanding of the impact of today's technologies. To do that, the researcher considered studying information system theories and how they allow the development of the suggested research model. Common theories include but are not limited to Actor-network theory, STT theory, social capital model, The structure theory, task-specific technology, Theory of responsive adaptation, Adaptive enterprise theory, Behavioural decision theory, Complexity theory, Critical social theory, Technology acceptance model, Theory of reasoned action, Customer focus theory and the Unified Theory of acceptance Theory of planned behaviour. Investigating the above theories allows the researcher to understand those theories more deeply. Thus, the social and technical aspects were selected to have further investigation.

Taking into consideration the social aspects of the model that has been suggested, the researcher discovered that TAM is the most adopted theory in accepting new technology since our model has the sub-construct of accepting and adapting to new big data technologies. These sub-constructs involve how people (for example, IT staff within Saudi universities) deal with the new technology. Thus, the author decided to include the behaviour norms discussed in-depth in the action reasoned theory, subsequently analysed planned behaviour theory and included it into its new technology acceptance model. Thus, the above theories assist the researcher to select social factors to obtain further investigations of those social factors in supporting big data analytics in Saudi higher education.

In the light of the technical subsystem of the proposed model that includes big data system quality and big data tasks, the researcher found that key constructs which will be selected in this study are discussed in the sociotechnical theory—also, the information system success model, in particular, system quality. As a result, we proposed a model that combines the precepts of the sociotechnical theory with the information system success model developed by Delone and Mcleans. The discussion and evaluation of these theories are discussed in the following sections. Figure 3.1 illustrate the actions taken to generate the research model.

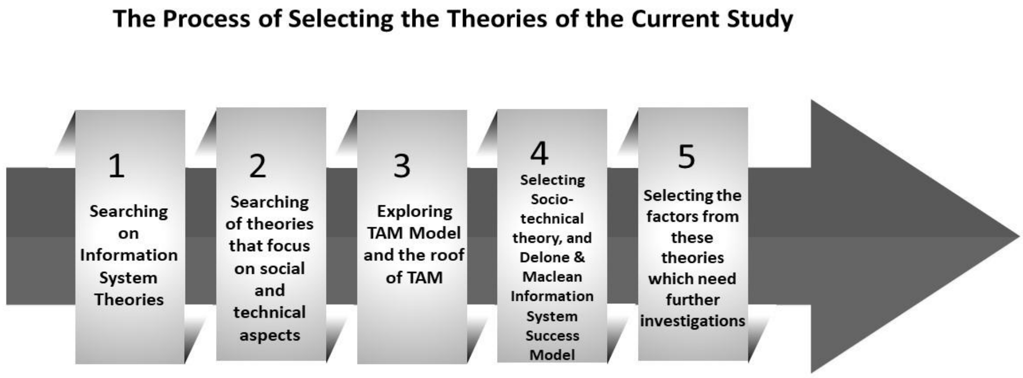

Figure 3.2. **The Process of Selecting the Theories for this Study**

3.2.1. Theory of reasoned action (TRA)

The theory of reasoned action theory was introduced in (1975), which aims to clarify how attitudes and behaviours in human action are connected, which are developed from an individual's perspective on an act and their own subjective norms. Attitude can be defined as either positive or negative thoughts held by the individual performing a behaviour. Likewise, the subjective norm concern perceived social pressure to act or not act in a particular manner. (Ajzen & Fishbein 1975). The attitudinal and behavioural variables are explained by action, target, context and time (Ajzen & Fishbein 1975). Subsequently, TRA attempts to clarify the logical actions occurring in a particular situation. Also, TRA can deduce how a person will act from the previous attitude towards that matter. The decisions of the person to participate in a particular activity are shaped by anticipated consequences or outcome evaluation. The TRA model is shown in Figure 3.2. Below incorporates behavioural intentions because personal norms greatly influence personal behaviours.

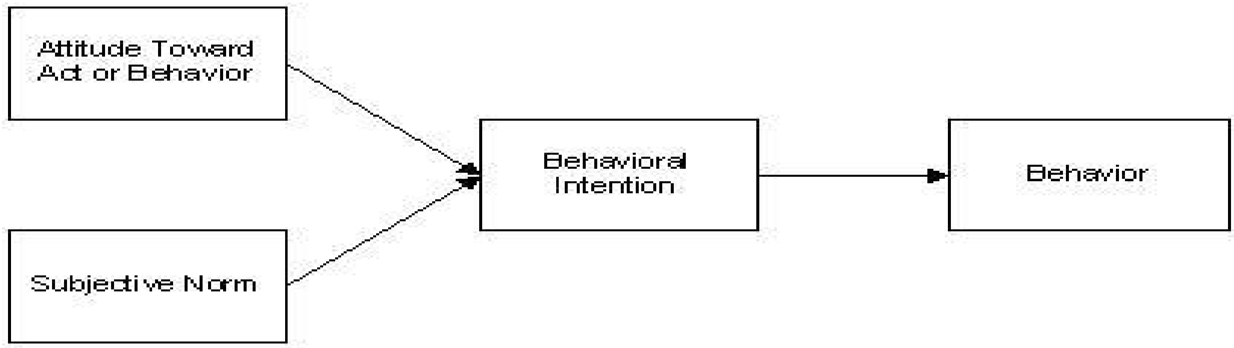

Figure 3.2: Theory of Reasoned Actions

TRA and TPB highlight the connection between behavioural intention and the users' behaviour in using the technology. However, they are widely criticised due to their poor predictability of behavioural intention (Montaño 1992). Prior researchers stated that weak predictability of behaviour intention resulted from people's beliefs instead of the events themselves (Ajzen & Fishbein, 1988). Abouassar (2017) believed that the interrelation between the construct does not always determine the effect of one over another. The revised version of TRA, TPB, is presented in the following sections.

3.2.2 Theory of planned behaviour (TPB)

The criticisms regarding the beliefs of people that were presented in TRA were the motivation behind the creation of TPB. In furthering their argument, Ajzen & Fishbein added perceived behaviour control to their model. Besides, TRA factors are closely associated with the idea that an object's characteristics or qualities shape a person's attitude towards it (Ajzen, 1991). Hence, when people believe they are being controlled or manipulated in their perceptions or acts, their behaviour toward an object changes as well (Ajzen & Fishbein, 1988; Lai, 2019). Such changes in behaviour frequently affect a person's belief about an entity. Thus, altering the person's attitude towards behavioural intention (BI) is critical. This abnormal result in perceived behavioural control (PCB) and perception is also one of the TRA model's most significant flaws. TPB incorporates perceived behavioural influence as a BI construct (Montaño, 2015; Asare, 2019).

Equally important, perceived behavioural control is the most imperative factor that affects BI (Asare 2019; Sheppard et al. 1988). For instance, when people have a positive feeling about a particular object, their attitude toward that subject also rises, or vice versa

(Sheppard et al. 1988). This strong connection between people's attitudes and perceived behavioural controls impacts an individual's ambition performance (Abbasi et al., 2021).

Although a person's attitude plays a crucial role in their actions (Ajzen & Fishbein, 1988), other essential aspects, like age and individual variations, play imperative roles in predicting people's behaviour. As a result, those other vital factors are explored and investigated in various theories, i.e., TAM, TAM2, and TAM3, which will be discussed in the following sections.

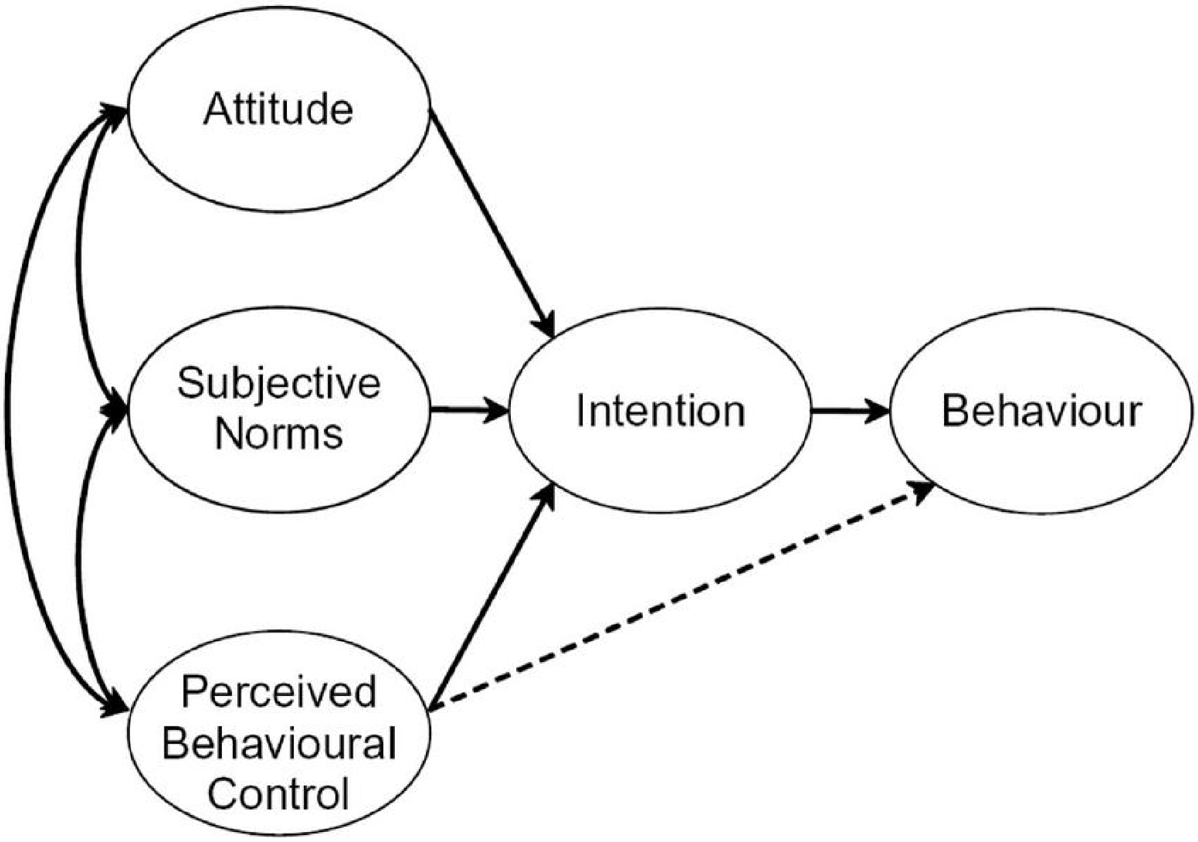

Figure 3.3. TPB Theory Ajzen & Fishbein (1988)

3.2.3 Technology Acceptance Framework

Davis is the founder of Technology Acceptance Model (1989). This Model is merging factors of TRA and TPB, aiming to clarify the formulation of computer adoption, increasing the reliability of users' behaviour among various computing systems and user environments. As a consequence of this, the simple TAM model included and evaluated two hypotheses: perceived usefulness and perceived easy to use. A system's usefulness can be defined by how effectively it helps users perform their jobs or how significantly it boosts the quality of their results. Besides, Ease of use is defined as how the system is easy to use by the end user.

Undeniably, external elements influence the usefulness and usability of the system. These factors describe demographics, behaviours, and referents'. It's possible that the perceived usefulness and ease of use of external variables have an indirect effect on the desire to use them. The perceived utility is theorised to be closely related to perceived ease of usage; therefore, systems should be designed with the idea that they would be more functional if they were easier to use (Venkatesh 2000; Pringle 2020).

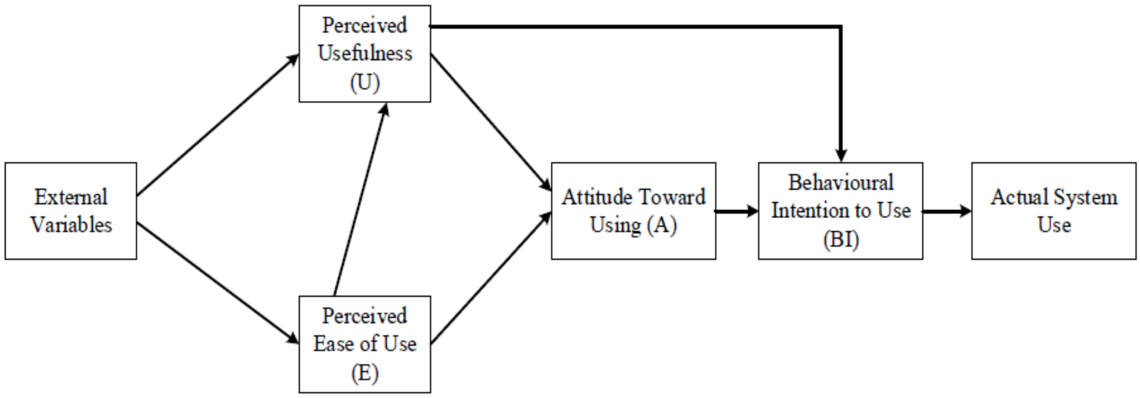

Figure 3.4: **TAM Model (Davis et al., 1989)**

Although TAM is broadly applied in technology adoption studies, several weaknesses have been raised. TAM is accused of using self-reported data instead of accurate data. Utilising self-reported measurements can compromise the correlation between the dependent and independent variables. While other significant limitations include not considering the social and individual influences on behaviour (Ajibade 2019).

3.2.4 Technology Acceptance Framework TAM 2

Venkatesh and Davis are credited with the development of TAM2, which is an improved version of TAM1 (2000). The perceived usefulness in TAM 2 was based on social influences involving subjective norms, voluntariness, and images (Venkatesh 2000). The subject norm is a social mechanism affecting perceived usefulness and intentions. This subjective concept of effect on behavioural intentions is derived from the idea that individuals will follow behaviours if they are seen to be suitable by others, even if they do not engage with them (Taherdoost 2018). Subject norms were tested in various experiments using optional or mandatory use; for instance, in (Barki & Hartwick 1994). There was only a substantial correlation between expectations and behavioural intention in mandatory environments. Then, voluntariness moderates the impact of normative perceptions on intentions (Venkatesh 2000).

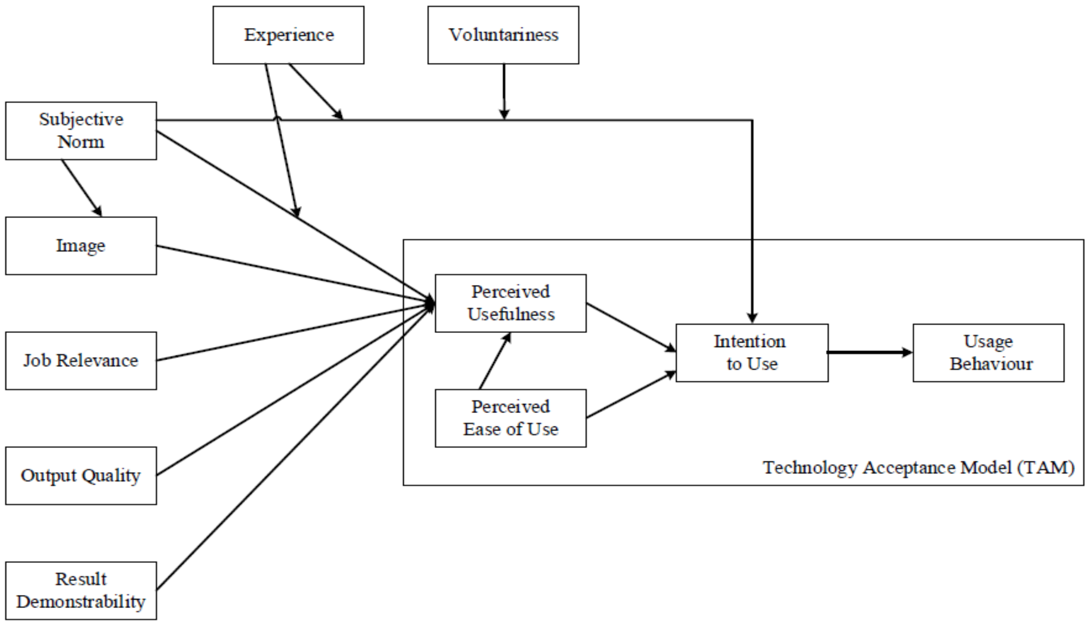

Figure 3.5. **TAM 2 (Venkatesh 2000)**

While TAM2 attempted to solve the weaknesses of TAM1, it invariably holds some limitations of TAM1, such as failing to mention external factors such as the sense of user-friendliness (Lai 2017). The persistent limitations prompted a third attempt at fitting the theory.

3.2.5 Technology Acceptance Framework TAM 3

In 2008 Venkatesh and Bala proposed TAM3, as illustrated in Figure 3.6, by combining TAM2 and TAM. TAM3 proposed several unique factors that contribute to PU and PEOU TAM3. The founders argued that all three versions could be interconnected such that the predictors of technologies utilised behaviour include the user's knowledge (experience). The fear of computer use (computer anxiety) would also impact perceived ease of use and consequently, perceived ease of use will impact behavioural intention.

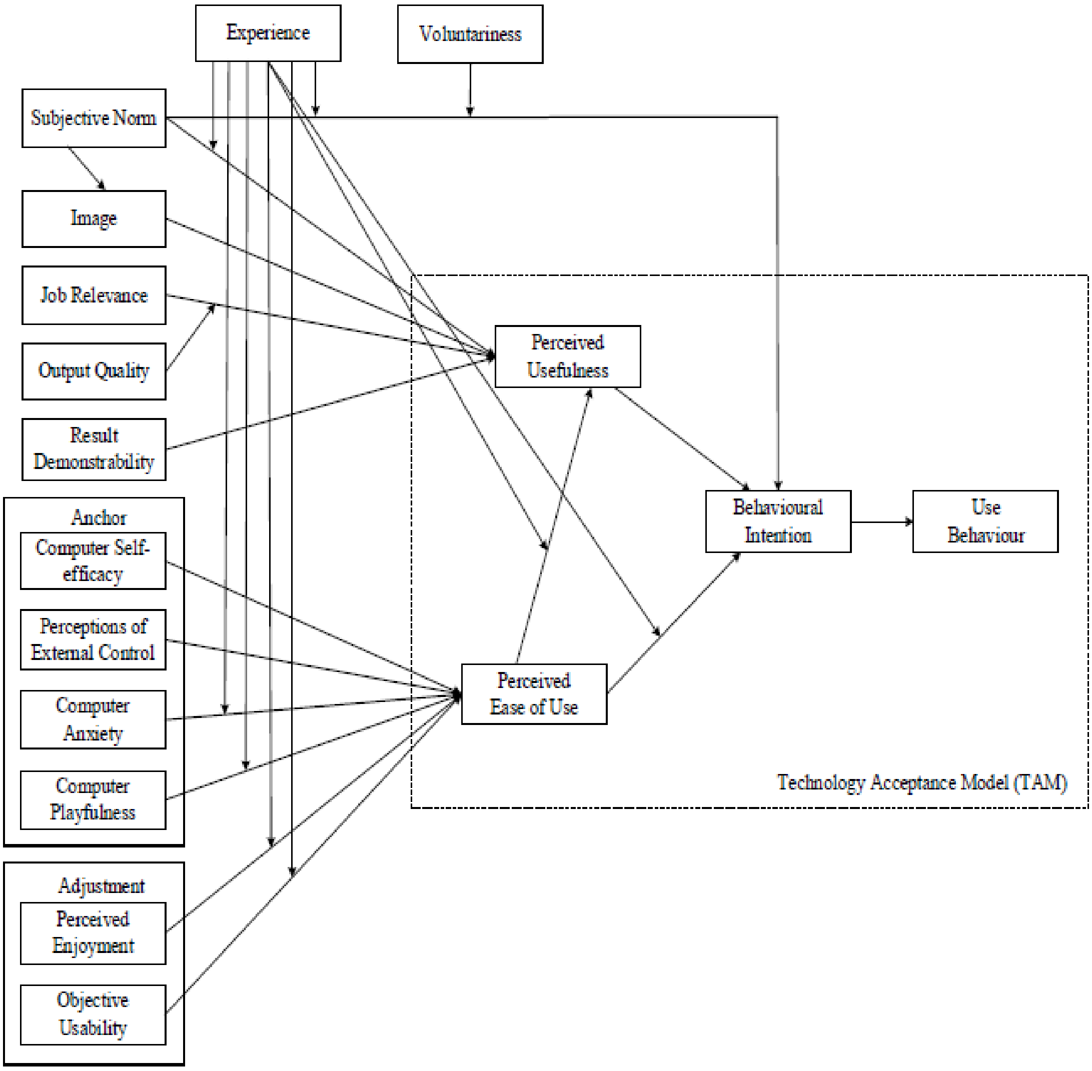

Figure 3.6.**TAM 3 (Venkatesh & Bala 2008).**

To obtain further investigation of the factors that were examined in TAM3, Venkatesh and Bala (2008) conducted an investigation that lasted for five months, involved 156 participants, and involved four different organisations. All variables correlated to user experience produced Cronbach's Alpha values of more than 70%. Venkatesh & Bala (2008) demonstrated that customer experience significantly influences modern technology, which calls on administrators to balance the newly invented technology. Overall, TAM underlines the distinctive roles and specific mechanisms associated with PU and PEOU and claims that the user's perception of utility does not affect the ease of use (Venkatesh & Bala 2008).

3.3. Theories Utilised in This Study

After reviewing and examining relevant theories discussed above, and the overview of profound and standard theories of technology adoption and use in the preceding section, this section delves into the theories that shape our research model. The socio- technical theory (Cherns 1977) provides the foundation for our arguments on using BDA for decision-making. Furthermore, the success of information systems models of DeLone and Mclean was also introduced to identify the critical aspects of the technical realm defined in the social-technical theory.

3.3.1. Socio-technical theory

STT theory is critical theory which widely applied in information systems research and the basis for the arguments of this study. Cherns (1976) found that the socio-technical theory posits that implementing a new system may indeed be integrated with human elements such as tasks, regulations, and culture to meet organisational objectives. The theory originated from revolutionary work at the Tailstock Institute in London and has been continued throughout the World (Sony & Naik 2020). The cornerstone of this theory is the combination of human, technical, and organisation aspects in investigating how information technologies are used in organisations. The critical argument is that new systems require the interactions of social aspects, such as people, and organisational culture with technical factors, such as tasks and technology (Mvungi 2018).

The socio-technical theory focuses on the social subsystem, which consists of people & relationships, whereas the technical subsystem includes elements and technology (Cherns 1977). The combination of these components resulted in the developing complex information systems. The social subsystem involves individuals' changing priorities and perceptions about job roles which force adjustments in organisational design. On the other hand, technological advancements contribute to shifts in beliefs, cognitive systems, life patterns, environments, and interactions, all of which profoundly impact a society's development and sustainability capacity (Spear and Bowen 1999).

Advancing the social-technical theory, Lai (2017) provided factors that transform work systems, which include technical, personnel subsystem, organisation structure, and external environment. Technical factors involve many components, including technology, regulations, and practices that define processing methods, the behaviour people take on an object while conducting tasks, and the approach for minimising operation instability (Sony and Naik, 2020; Emery, 2016). The social factors include workforce demographics and psychosocial factors of the workforce, including the behaviour of the staff in performing specific tasks, the work environment, the expertise of completing the work, and the motivation toward accomplishing the task.

The organisational structure is an imperative factor of the social subsystem that highlights centralisation, formalisation, and complexity (Malatji 2019; Wu et al. 2015). While centralisation refers to the strategic, tactical, and practical decision-making process, formalisation refers to standardising organisational tasks and jobs. The work environment argument by Lai (2017) relates to organisational characteristics that control work operations. Besides, social-economic, educational level, political, and cultural factors influence the organisational environment. These factors differ in quality, type, and importance (Prior 2020).

While we know the two tenets of the theory, to ensure the best possible performance, Trist (1980) argued that enhancing one aspect of a social, technical framework requires enhancing the others. This is defined as joint optimisation and aims to improve employee efficiency and positive interactions (Carayon et al. 2015; Osthuizen & Pretorius 2016; Salehi et al. 2021). Generally, the foundation of STT theory is to integrate the social with technical factors of an organisation's structure and methods necessary to create the joint optimum condition that combines these four essential sociotechnical theory aspects. Thus, focusing primarily on the social or technological component within the organisation would only enhance the performance of a single component of the system (Sekgweleo & Makovhololo 2019).

The significance of joint optimisation as a pillar and the base of socio-technical systems theory becomes obvious (Malatji 2019). In fact, according to Troyer (2017), interpersonal relationships, processes, and technologies are often complicated recursive, and difficult to estimate. Undoubtedly, the theory reflects a distinct collection of ideas and principles concerning the interdependence of a system's social and technological aspects. Sony & Naik (2020) suggested that organisations should consider the importance of social and technical aspects in gaining the benefits of organisational systems. The organisation, however, is considered the complex aspect of this theory (Daryani & Amini 2016; Mamohtob 2019). Nonetheless, numerous scholars have explored the overall framework of sociotechnical theory and the factors that affect its diverse social and technological aspects in different ways. Figure 3.7 illustrates the factors of sociotechnical theory.

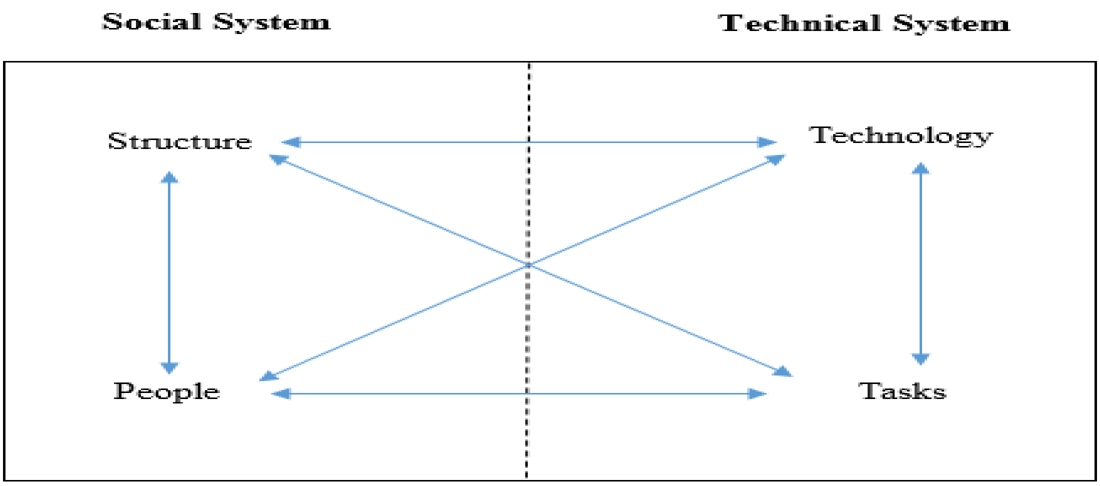

Figure 3.7. Sociotechnical theory (Bostrom & Heinen 1977).

The social dimension's organisational structure offers features that facilitate control, communication, and workflow systems. People (Big data Performers) directly connected to the enterprise system, such as top management, who control or conduct job tasks are called 'actors' (Emery 2016). Two capacity domains make up the technological component of work activities; technology (tools and resources) (tasks) (Bostrom & Heinen 1977). The technological dimension's 'technology' capacity domain provides the tools and services necessary to conduct job duties, while 'job activities' are the basic daily organisational tasks performed through social amenities. The following table summarises the characteristics of each social and technological system dimension.

Table 3.1. Characteristics of Socio-Technical Systems Adopted from (Malatji 2019)

Dimension	Attributes
Social Element Organisational Structure (Organisational Culture)	Abilities/capabilities; Values and standards; Behavioural patterns; Cultural knowledge; Structural management.

Actors (People)	Individual/staff and relationship workgroup
Technical Dimension (tool & resources)	Technology; Applications; Hardware; Tools; Data Management tool; System Functionality; System Quality
Work Activities (Tasks)	Daily Tasks; Data Security; Privacy; Data Quality
Environmental Dimensions	Political situation; Economic; Social; Government Regulation; Consumers; Natural Disasters; Environment; Relationship; Other external factors

While the STS theory revealed the social dimension of organisational systems, researchers highlighted numerous challenges aligned with adopting the theory (Bach 2017; Prior 2020). Here we briefly highlight the key concerns surrounding the STS theory. The inconsistent wording usage could confuse potential STS adopters. The conflict between behaviourism (employee) and administrative principles. Also, the levels of abstraction where managers and workers may also be cautious of socio-technical ideas in certain situations, with prior presenting managers actively and the latter applying humanistic values—using various abstractions to describe the same structure, primarily because the system boundaries are drawn in different areas. Third, the shortage of agreement performance standards and the feasibility of using STS methods have received little scrutiny. Analysis without synthesis raises another concern: the STS methods have always been used to analyse and criticise current and ineffective processes without proposing alternatives. Lastly, Potential anachronism: Rejection to follow up with technological advances and organisational changes may make STS methods look dated.

Apart from the STS approach challenges mentioned above, Mumford (2006) found that different STS approaches have different characteristics. According to Salehi et al. (2021), the negative aspects of STS approaches are problem description, understanding the significance of humans, interpretation of philosophical concepts, and the application of methodologies. Such problems may demonstrate why numerous executives recognise the importance of sociotechnical concepts and the existence of STS in the actual world.

3.3.1.1. Socio-Technical System (STS) models

In the last decade, there has been an apparent effort to outline the benefits of sociotechnical theory to unravel issues associated with managing the information system. A study revealed how the sociotechnical approach resolved the failure of MIS in a prominent newspaper company and revamped the MIS scheme by assimilation of the technical factors and the people who interact with the new system (Dremel et al. 2018). Similarly, Townsend (2015) explored the flaw in the published studies on infrastructure re-design methods in which several views were raised. For instance, most re-design methods are based on technological artefacts rather than socio-technical processes. Established frameworks are not explicitly applicable to sociotechnical methods, varying from technical artifacts to how employees execute the system in a group setting. As a result, engineers may not fulfil their obligations for re-designing socio-technical structures, which is particularly important in the practice of systems engineering. The study concludes that the human factor is imperative for re-design engineers in advancing the use of STT systems within firms.

Another research examined the significance of social media in establishing relationships with customers in commercial sectors. Using the lens of STT to view the results taken from the case bank's e-banking customer base, the study suggests that social network has the power to radically modify bank-client relationships and contribute positively to the extent the parties communicate with others. A demographic factor such as age is the only critical factor for the worthiness of social network platforms such as Facebook for a bank (Oesterreich & Teuteberg 2019). Findings among users aged 15-30 saw up-to-date information as the key benefit of having their bank on social media, while those aged 31-60 desired different returns.

Additionally, a qualitative study using grounded theory investigated the lack of technology adoption in intensive care rooms in a private university. The study's architecture was influenced by a theoretical paradigm of sociotechnical philosophy, a coherent theory of technology adoption and usage, and corporate culture and transformation. The researcher discussed the particular issue of healthcare organisations' noncompliance with CDC-P hand hygiene guidelines, which increases the likelihood of healthcare-associated diseases due to a lack of proper technology use. The result showed that technology, leadership (top management), and patient safety culture positively impact the use of technology within intensive care rooms in university teaching hospitals (Augustine Lyndon Garvin 2018).

According to Mvungi (2018), previous studies used social-technical systems in system engineering without notable achievements due to insufficient techniques during the implementation of information systems. The author highlighted the significance of other vital aspects that shaped organisation systems, such as social environments. The proposed study provides a new sociotechnical framework that attracts software engineers/system developers to use the designed approach. The authors asserted that the newly designed approach could help developers implement successful information systems.

Furthermore, Harris (2019) investigated the Agile framework creation best practices that cybersecurity leadership could employ to create a cyber-resilient information system in the department of defence (DoD). The study applied the sociotechnical theory to implement an intelligence system for the DoD. Semi-structured, in-depth interviews were conducted to gain more understanding of the phenomenon being investigated. The result revealed that cybersecurity and procurement leaders proposed best practices emphasised the importance of optimising for both social (individuals and culture) and technological (tasks and processes) dimensions of security and that leaders need to develop a cyber-resilient system. The eight highlighted themes (best practices) included: (a) performing active participation; (b) participating in information security; (c) eliminating complexity and organisational obstacles; (d) addressing issues about organising, learning, and supplying; (e) recognising that agility is not a magic bullet; (f) evaluating, identifying, and risk management; and (g) guiding the acquisition of timely, scalable, and cost-effective solutions.

Despite the artificial intelligence-controlled information security, 90% of disruptive cyber threats are derived from human behaviour or faults (Malatji 2019). The above studies have also demonstrated that humans are the weakest source of data leaks in information security. Reports indicate that many businesses continue to take an unnecessarily technocentric approach to cyber-attacks; this approach increases the likelihood of not understanding the whole image of cyberattacks. STT approach was utilised in the study to explore the factors that increased cybersecurity attacks. The researcher founds that the stakeholder management for collaborative protection engineering will support the network of professionals in information security, cybersecurity, and information systems compliance through critically optimising information system security practices (Ghafir et al., 2018).

Additionally, the leadership process will help those who conduct business system security at the functional (governance) and operational (directive) stages, allowing for collaborative organisational security optimisation (various levels within the organisation) (Malatji 2019). Figure 3.8 illustrates some of the previous studies that utilised social-technical systems.

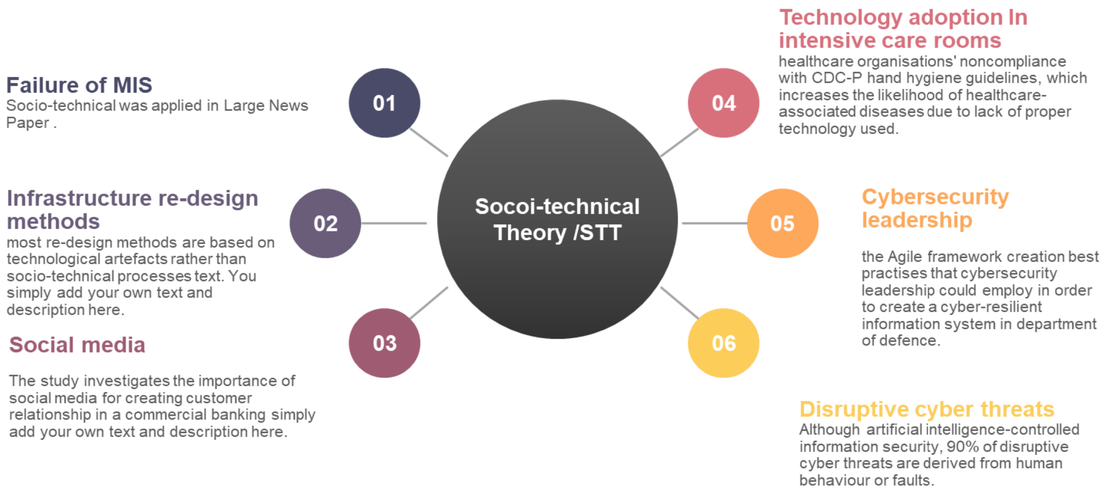

Figure 3.8. **Previous Studies based on STT**

Most research attempts to investigate the failure of implementing information systems based on STT, like those associated with human safety, such as a system implemented in intensive care rooms. Others discussed the failure of developing the DoD information system. Besides, implementing BDA systems in educational sectors is not less important than the implemented systems mentioned above. Although there is a lack of literature on the application of STT in investigating BDA, a few studies have explored the uniting of social and technical aspects.

3.3.1.2. Social Technical System (STS) and Data Analytics

In big data analytics, sociotechnical theories transcend the data, technology, and people. According to the STS, humans and machines are not inherently at odds but can coexist in beneficial ways (Geels, 2022). This theory allows for collecting and processing large amounts of data without losing quality while also allowing humans to be involved in the process and decide what should be done with the information. The socio-technical approach effectively analyses and manages big data systems because it investigates the technological and human components. While the technology component involves developing new tools or methods for analysing voluminous, complex data quickly and efficiently, the human component involves training employees on how to use big data tools and methods productively (Kivimaa et al., 2022).

The theory helps organisations understand what makes for good design and development practices when building products that use big data: from understanding human behaviour and preferences to understanding how people use technology (Lee et al., 2022). Organisations can cope with big data management problems that are difficult to manage due to their various dimensions without needing sophisticated technical skills. Such an approach is based on a detailed understanding of organisations' current business practices, which in turn requires an investigation of organisational culture and social relations that naturally affect people's behaviours towards data (Münch et al., 2022).

There is also a need to understand the limits of data analytics in discussing the ethical considerations related to the use of information systems dealing with sensitive or private data (Ghaffarian, 2011). The limits related to the constraints imposed by human psychosocial factors on the information systems developed with technological determinism. These limitations challenge potential users because their perception of these elements can vary depending on how they interpret them. Therefore, people feel more comfortable when they can understand what information systems can produce and what type of results they can achieve while at the same time having some control over it all.

BDA has attracted academics and practitioners to establish the benefits of applying sociotechnical theory in the field. One such attempt is built on a suggestive case study in which researchers determined BDA actualisation mechanisms as improving, constructing, and integrating, manifesting on these levels, i.e., technology actor and the structure (Dremel et al. 2018). After investigating the actualisation of four big data analytics capabilities at an automobile manufacturer, the firm; authors concluded that the sociotechnical perspective frames actualisation. As the mechanism of repetitive moulding of social and technological entities; it allows the researcher to uncover evidence of gradual and essential understanding at both, the organisation and individuals. (Dremel et al., 2018).

Equally important, Cronemberger (2018) asserted that government agencies in the United States and worldwide rapidly use data analytics to facilitate decision-making. However, the researchers focused little on how data analytics methods, strategies, and findings are used by various actors (producers and consumers) within governments. Instead, the study investigated the primary factors that affect data analytics use from a socio-technical perspective, namely the significance of data, top management, and social factors. Notably, information exchange between local governments plays a role in resolving data access issues, conceptualising and reframing questions, and gaining insights into data analytics outcomes.

Günther et al. (2017) posited that big data analytics development in recent years emphasises technical aspects; therefore, there is a lack of understanding of potential social and economic values. The study followed a sociotechnical perspective and found two sociotechnical characteristics of big data that impact meaning realisation: portability and interconnectedness. Overall, we contend that organisations must constantly realign their work processes, corporate structures, and investor priorities to realise the value of big data.

3.3.2. Information System Success Model

Various research on information systems also makes extensive use of the model developed by DeLone & McLean. First developed in 1992, the model offers a multidimensional assessment of system success involving interrelations among the various success categories (Grover et al. 1992). After another decade had passed, the model was revised to include a total of six dimensions: information, system, service quality, user satisfaction, and perceived net benefit (DeLone & McLean 2003).

They have provided a framework for determining how effectively information systems are used, given that their development and use are associated with substantial capital investment. The model was also motivated by the almost imminent failure of IT projects. Beyond the investments, a system is expected to deliver the intended value to the organisation and its clientele. The model was initially tested in e-commerce applications but subsequently validated in various information systems contexts – such as hospital information systems (Ojo, 2017), digital libraries (Alzahrani et al., 2019), E-Learning systems (Yakubu & Dasuki, 2018), E-Government (Wang & Liao, 2008), call centre (Baraka et al., 2013), industrial system (Roky & Meriouh, 2015), and many others. Though widely tested, it remains uncertain whether the model would still be valid in the recent advances in disruptive and pervasive technologies.

While smart systems can create business value, their success is difficult to measure (Chasalow & Baker, 2015; Visinescu & Visinescu, 2016). Information system success model was proposed as a solution to this problem in order to close the gap. To address this gap, a model for determining the effectiveness of information systems was developed, which has become extensively used and significant in the field. (Mkinga 2020; Zheng & Liang 2017). Furthermore, the efficiency of any information system depends on the information quality delivered by the system. As a result, information quality is considered the most significant aspect of any information system. (DeLone & McLean, 2003). The researchers DeLone and McLean hypothesised that consistency considerations influence users' feedback and usage desires and that system use is a predictor of the system's performance. Overall benefits are favourable operational consequences of the system. Figure 3.9 below illustrates Delone and Mclean model.

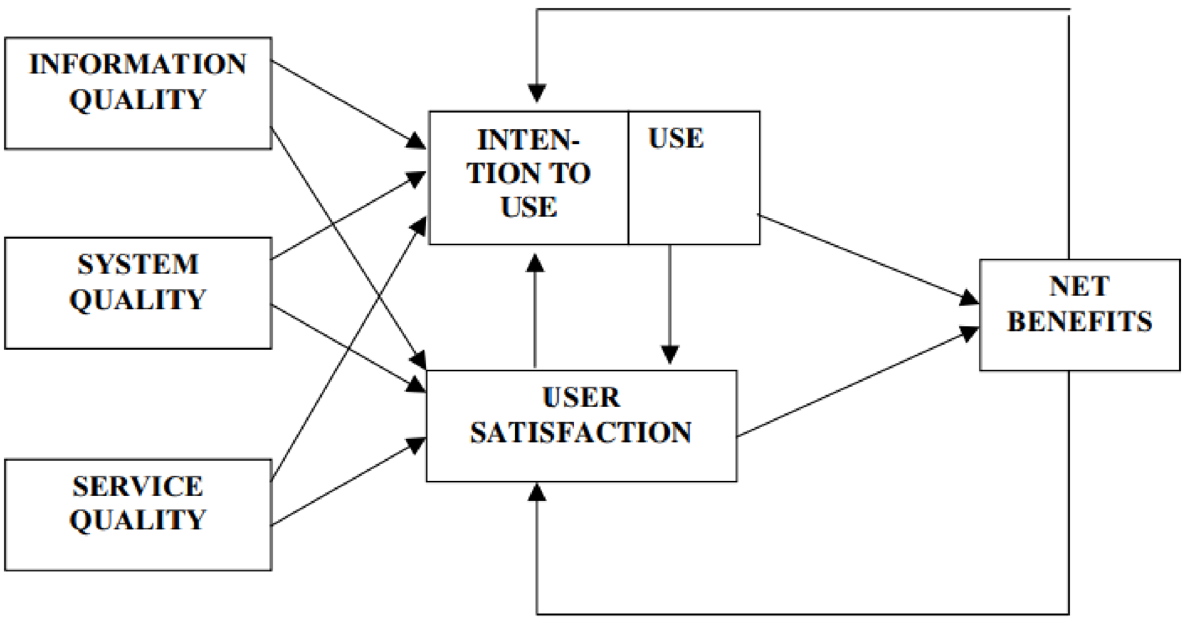

Figure 3.9. **Information System Success Model**

As illustrated in Figure 3.9, the information quality, the system quality, and the service are each presented as independent variables, not considered self-contained indicators of success but thought to be interdependent (Petter et al. 2008). Information quality represents the format and accuracy of data. System quality measures the ability of the system to produce effective data. Service quality relates to the system's services to the user. User satisfaction identifies the user's gratification toward the system, while net benefits denote the degree to which the interactions and feedback are associated with intent to use (DeLone & McLean 2003). The critical components of the IS performance model examined in the current research are the system quality that provides the security, privacy, and quality of analysed data that assist in decision-making.

3.3.2.1 DeLone and McLean Framework in Information Systems Research

There is no doubt regarding the significance of the information system success framework developed by DeLone and McLean, and previous investigations of system success employing this model have been reported. Montero (2019) stated that an intelligent system is a powerful tool that helps executives to make decisions based on analysed data provided by the system. This system is infrequently used due to the lack of understanding of other vital factors that facilitate system success. Montero used information system model to investigate how information and system quality in intelligence systems impact the success of business intelligence systems. The study found that quality indicators strongly correlate with the business intelligence system's effectiveness as determined by information use. Additionally, the results revealed that the connection between information and system quality and information use is moderated by maturity characteristics. Vander Weerdt (2018) conducted a similar study, looking at factors including system usage, how people rate the information quality and the effectiveness of organisational culture on the firm. The results also showed that information systems are affected by an organisation's culture, and there is a strong correlation between information quality and nett benefits from using the system.

In higher education institutions (HEIs), Tabbara (2016) examined the developments of ERP systems, which involved millions of dollars in enhancing strategy, incorporating performance management, automating established corporate practices, boosting competitiveness, and gaining a competitive edge. HEIs in the Arab Emirates followed suit and adopted ERP schemes to conform to the Ministry of Higher Education's requirements and achieve perceived benefits. With millions and endless hours invested in ERP schemes, UAE federal HEI executives have concerns regarding ERP return on investment. HEIs in the UAE defined and quantified the importance of ERP using DeLone and McLean's framework and learning organisation theory. The introduction of the post-implementation evaluation methodology showed some shortcomings information system success model and process quality constructs, along with Senge's learning structure constructs, which acted as impediments to fully realising ERP frameworks.

Similarly, Aldholay et al. (2018) argue that public organisations and institutions of higher learning are incorporating eLearning strategies to change how people study, participate in social activities and how institutions operate. Consequently, leadership is profoundly critical to the execution and progress of online education objectives. While scholars examined the acceptance in using online learning in different contexts, the DeLone and McLean progressing paradigm has not yet explored the mediating role of transformational leadership. Overall quality (system, information, and service quality) positively affects transformative leaders, ultimately shaping overall usage. However, performance has an insignificant effect on actual use, even in the presence of transformative leaders. Actual usage is essential because it impacts user satisfaction and performance. Similarly, Mkinga (2020) asserted that since system performance is critical to achieving the organisation's goals, an assessment of system success is necessary to ensure that investment in information technology is worthwhile. Most of Tanzania's Higher Learning Institutions (HLIs) have embraced information technology to provide services to their clients.

Nonetheless, there is little evidence that system performance evaluations have been conducted to determine optimal attributes that enhance information system effectiveness. Mkinga (2020) used the information system success model to evaluate how effective the Student Information System (SIS) was at the Institute of Finance Management System. It was evident that the key influencers of system performance are its efficiency, quality of information, service quality, system utilisation, and customer satisfaction.

In healthcare services, Ojo (2017) used the model to examine hospital information systems in developing countries and noted that system quality affects both utilisation and user efficiency. Information Quality has a major impact on customer retention. Additionally, service efficiency has a statistically significant effect on utilisation and customer loyalty; however, customer loyalty has no discernible effect on expected net benefits. Additionally, while system usage may not affect customer satisfaction, it could affect expected net benefits. Notably, it was discovered that system efficiency and usage are critical indicators of healthcare system success; therefore, healthcare information systems should be simple to use, adaptable, and usable to achieve their primary purpose.

3.3.2.2 DeLone and Mclean IS success Model in Big Data Analytics Research

In this section, we take a look back at some of the earlier research on big data that used this framework. For instance, Ji-fan Ren et al. (2017) explored the efficiency dynamics associated with maximising market value and performance of the firm in a big data setting (FPER). It was observed that system consistency (system stability, usability, flexibility, interoperability, rapidity, confidentiality, and data quality is crucial for improving FPER in the context of BD. Additionally, big data market importance is a mechanism for quality and FPER. Ji-fan Ren et al. (2017) established a relationship between machine efficiency, information quality, market value, and FPER.

Adrian et al. (2018) stated that big data innovation enables several organisations to exploit future opportunities and strengths for success and decision-making. However, the effectiveness related to implementing big data analytics for improving decision-making has not been investigated. As a result, the goal of their research is to accomplish two things: first, they want to identify and evaluate the factors that influence BDA implementation. Second, the researchers want to propose a conceptual model for effective decision-making based on BDA implementation assessment. The paradigm is built on three dimensions: data plan execution (organisation), collective information worker execution (people), and analytics execution (technology). The results of the study are being used to develop a proposed framework that aligns with the hypothesis test and could eventually result in a more efficient evaluation model for effective decision-making.

According to Wamba et al. (2018) expressed that big data analytics (BDA) receives the majority of the coverage these days, and equally important—and maybe perhaps more so—is the quality of big data analytics (BDAQ). Although many businesses make a complete return on investment from BDA, some fail. Value trends and their overall effect on firm results are unexplained in the data economy. To build a BDAQ model, Fosso Wamba et al. (2018) draw on two significant theories—the resource-based perspective and information management consistency. The findings indicate a critical, constructive partnership between the BDAQ and firm results, with strategic alignment as a critical moderator. The next sections will discuss the justifications for applied theory of the current study.

3.4. Justifications of Applied Theories

Selecting the appropriate theory in information systems studies is vital. Most importantly, understanding the factors that suit the study's phenomena. For instance, previous studies explored the significance of technical aspects that could support BDA implementation and ignored the importance of social and environmental factors, which have equivalent significance on BDA (Abbasi et al. 2018). The authors also highlight the importance of people in implementing new technology, the interaction among people, the organisation's process, and structure. In the era of BDA, people play a crucial role in analysing and visualising big data for improving decision-making and creating business excellency (Mvungi 2018). Next section discusses the justifications of the selected theories for the current study.

3.4.1. Justifications for Applying Socio-technical Theory

Despite the extensive examination of big data technologies, argue that "When it comes to big data, a comprehensive sociotechnical strategy is necessary to overcome the obstacles that might arise within the realms of technology, people, and organisations." (Alharthi et al., 2017 p. 285). Big data analytics as new technology is impacted by social and technical factors, such as organisation's structure, technology, tasks, and people (Charif, 2017; Alharthi et al., 2017). The interaction of these factors forms the foundation of a socio-technical perspective. Dremel et al. (2018) explore BDA affordances at three different levels, technology that allows the firm to take advantage of BD, process, and the data-driven culture that tolerates the technology and process within the firm. They argue that implementing BDA requires critically observing the social and technical aspects to gain value. On the other hand, Sekgweleo & Makovhololo (2019) argue that theories such as ANT and AT are often utilised in information systems research; but while they add new insight, they are interestingly not founded on IS/IT theories but on sociology and psychology. The sociotechnical lens steers the processes of analysing, explaining, and forecasting phenomena and provides guidelines on how these sociotechnical aspects are utilised in implementing BDA. To this end, STT theory is sought to combine social and technical tenets of BDA for decision-making.

More precisely, the STT is mainly built from the interactions of technology, people, structure, and tasks. BDA in higher education context consists of (1) the technology that supports the storage, analysis, and visualisation of big data, (2) the people within the firm who analyse and visualise the data, (3) firm structure such as the organisational culture of accepting new technological improvements, and (4) tasks such as storing, analysing, and visualising big data. The interaction of those factors is critical to investigating the significance of BDA, which could improve decision-making. In the next section, the author will discuss the justifications of the second supported theory for this study.

3.4.2 Justifications for Applying Information System Success Model (DeLone and McLean)

The model developed by DeLone and McLean is the one that is used most frequently in information system research (Alsahli 2018). For instance, Adrian (2018) explored how information quality improved decision-making in BDA environments and indicated that data quality positively impacts the decision-making by executives. Likewise, Fosso Wamba et al. (2018) reported information quality, technology quality, and talent quality influence big data quality, which is central to BDA. Similarly, Ji- et al. (2017) explored information and system quality to identify the relationship between the two and their role in improving firm performance in BDA environments.

Furthermore, Fosso Wamba et al. (2018) and Ji-fan Ren et al. (2017) suggested further studies exploring the impact of system quality, which could be represented by data privacy and security, on improving firm performance. Moreover, Mcconnaughey & Member (2020) state that big data privacy and security are the main challenges in implementing BDA systems. They suggest future work on big data analytics should involve system quality, such as privacy and security. Learning from previous studies, we operationalise system quality with big data security and privacy and quality.

3.5 Research Conceptual Model

Our research model, which is founded on the theoretical framework covered in the preceding sections, illustrates the significance of human, organisational, and technological factors in terms of their impact on the decision-making and performance of higher education institutions (HEIs). For instance, prior research has intensively asserted that human factors are the most critical aspect in creativity, innovation, and the development of new ideas (Aldholay et al. 2018; Bishop 2019; George 2015; Günther et al. 2017; Gupta & George 2016; *Liber* 2017). Besides human factors, studies revealed the importance of culture within the firm at different levels. For instance, Alattas (2020) discussed the significance of organisational culture and knowledge sharing in improving the system's success. Besides, Thirathon et al. (2017) explored how the culture of BDA enhances the decisions of executive staff. The researcher interviewed IT managers in numerous Australian firms to explore the significance of IT managers' culture in their decision-making process.

In addition to human and organisational cultural factors, the technological aspects are the third dimension of the proposed conceptual model. Technology plays an imperative role within the organisation as numerous studies have investigated the significance of technologies for gaining competitive advantages and achieving organisation goals (Hall et al. 2020.; Oosthuizen and Pretorius 2016; Ashraf & Verner 2017; Seidel et al. 2017). Big data analytics tasks, includes storing, analysing, and visualising data, are considered the fourth dimension of the proposed BDA conceptual model. Tasks are essential for driving "data-driven" decisions rather than experience (Khan et al. 2017). The conceptualised outcomes include improving the decisions of executives and firm performance. Data-driven decisions promote "better decisions" at the top management level (Passi 2021).

Besides, this study highlights the factors for improved executive decisions and explores the influence of human, organisational culture, and technological factors in implementing BDA. The factors are argued to improve strategic decision-making in HEIs. Figure 3.10

illustrates our research model, and the definition of concepts is summarised in Table 3.2. See Appendix M for detailed construct, definitions, supported studies, related research questions and Hypothesis

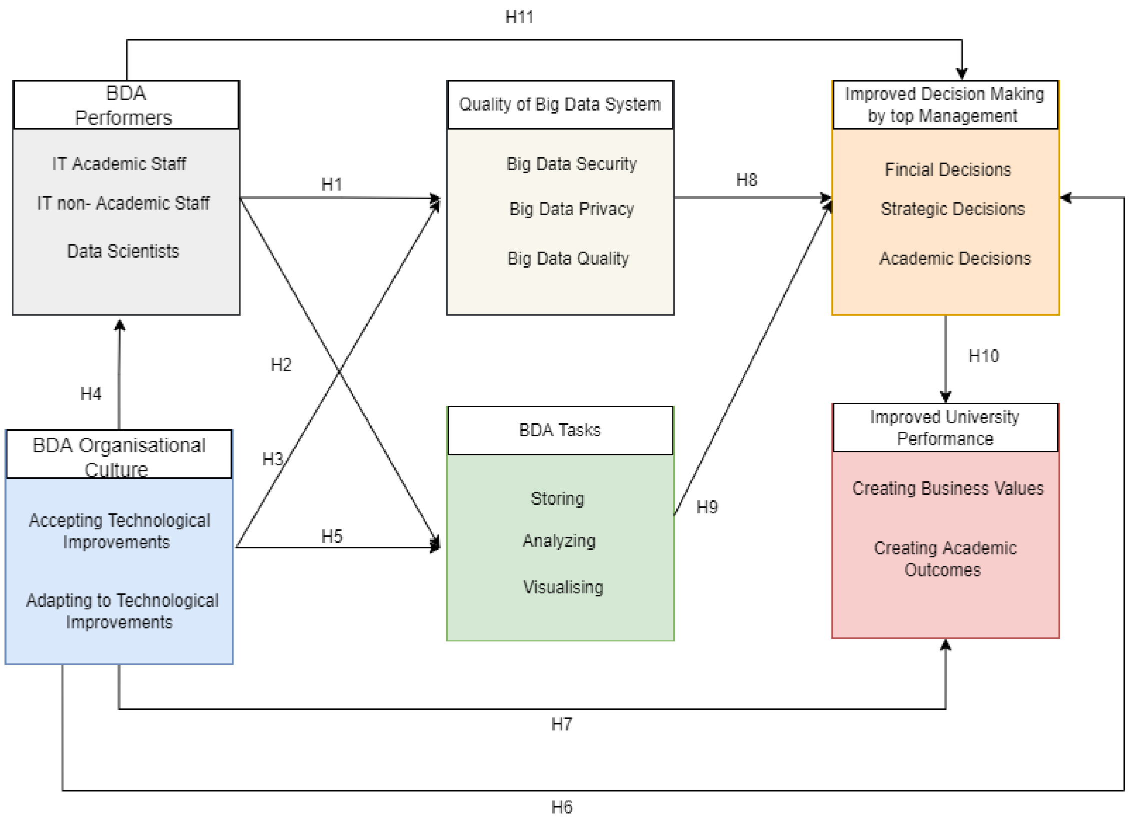

Figure 3.10. **Research Model**

Table 3.2. Definitions of the model constructs.

Construct	Description	Source
BDA Performers	- IT Staff responsibility for the security and privacy of BD - Data Scientists for BD Quality- BD Tasks.	(Bostrom and Heinen (1977) (Davenport et al. (2012) (Niederman et al. 2016). Dremel et al. (2018) (Charif 2017)
Organisational Culture	- Accepting and Adapting to new BD technological improvements (security, privacy, and big data quality)	(Bostrom and Heinen 1977) (Cronemberger 2018)

	- Accepting and Adapting BD technological improvements - Accepting and Adapting BD technological improvements	(Sam and Chatwin 2019).
Quality of big data system	- System functionality that provides big data security - System functionality that provides big data privacy - System functionality that provides good data quality	(DeLone & McLean 2003) (Fosso Wamba et al. 2018) (Cronemberger 2018)
Big data tasks	- Big data tasks include data capturing big data from various resources, analysing it and visualising it for decision making	(Bostrom and Heinen 1977) (Saggi & Jain 2018; Korherr & Kanbach 2021)
Improving decision-making	- Financial decisions - Strategic decisions - Academic decisions	(Bostrom and Heinen 1977) (Frisk and Bannister 2017) (Janssen et al. 2017) (Adrian et al., 2018)
Improving the university's performance	Decision-making that is informed by data has the potential to improve institutional performance by -Adding value to a company's operations -Developing successful academic outcomes	(Bostrom and Heinen 1977) (Saggi & Jain 2018; Korherr & Kanbach 2021)

3.6 Hypothesis Development

The aim of this study is to explore how the sociotechnical framework of big data analytics influences the decision-making process carried out by senior administration at Saudi Arabian educational institutions. We proposed hypotheses on the potential effects of several dimensions to achieve this goal, as discussed in the subsequent sections.

3.6.1 Big Data Performers and System Quality

The social system refers to the people and the organisational structure (Cronemberger 2018). The BDA social system will consist of BDA performers and big data-oriented organisational culture; the two factors are assumed to supersede technological barriers in big data (Alharthi et al., 2017). Recognising the co-evolution of IT and people is critical because the latter represents a component of the STT model that links the IT, the information, and the work processes (Niederman et al. 2016). Considering higher education, for example, BDA performers will include the academic as users and non-academic IT staff as users and administrators. In such a case, previous studies argue that IT staff impact the security of information systems (Sivarajah et al. 2017). BDA system, like any other IT system, are affected by the people that use and maintain them. (Russom 2011).

As academic and non-academic (technical staff), data scientists are key BDA players and are often in high demand. These highly skilled experts require a strong background in "arithmetic, analytics, mathematics, and computer science" (Cohen & Buboltz 2011). Data scientists, in particular, must perform the work of revealing patterns in the data, recognising trends, or discovering valuable knowledge from data; this is critical for any company hoping to benefit from big data (Estridge 2018). Data scientists are experts in big data technologies, programming languages, and procedures, but they must also be business savvy to design models that can be applied to real-world problems. As a result, qualified individuals are few, making recruitment difficult and costly.

On the other hand, data scientists are skilled and qualified employees who transfer the raw data into insight for business advancements (Adrian et al., 2018). Besides, data scientists enhance big data efficiency, improving decision-making (De Mauro et al. 2016). Song and Zhu (2018) highlighted the data scientists' role in storing the data, performing data analysis, and visualising analysed data that assists exclusives in making their decisions. Orenstein, Ladik, and Rainford (2016) indicated that a significant component of utilising big data within organisations would be data collecting and analytics and visualising those data. We hypothesise that:

H1: Big data analytic performers, including IT staff and data scientists, have a positive effect on System quality, i.e., security, privacy, and quality.

Figure 3.11: Hypothesis 1

3.6.2. Big Data Performers and Big Data Tasks

The firm's ability to collect and store data is a core aspect of BDA's capabilities and benefits; however, it is frustrated by data bias, the assessment process, and the impacts of the evaluation-related action. Manipulation in data gathering could affect derived value. Also, data origins must be considered, particularly in the reliability of collected data. Data collection also revolves around volume, variety and veracity (Cappa et al., 2021; Wamba et al., 2015). While big data tasks are evident, researchers have emphasised the role of data scientists in achieving these tasks. For instance, Herschel & Miori (2017) defined big data as the activities related to storing, analysing, and visualising big data; human "data scientists" and machines perform those activities to generate insights.

Similarly, Kim et al. (2016) stated that the tasks performed by data scientists fall into three general categories: data gathering, data analysis, and data use and dissemination. Though not exhaustive, the identified tasks denote the exclusive connection between people and key big data activities. Generally, people working with big data are expected to acquire adequate analytical skills, which could severely cripple their ability to generate useful insights and value (Alharthi et al., 2017). Besides, data scientists, for example, are vital in working with voluminous and complex datasets, optimising the data and discovering knowledge, ultimately resulting in value creation. To use Big Data effectively, the data scientist must first clean and organise the data (data storage, analysis, and visualise data) (Mckibbin & Member 2019). However, many key Big Data approaches are not part of statistical expertise, so statisticians cannot fill the gap.

In their article, "beyond data scientists. De Mauro et al. (2016) argue that a heterogonous nature of skills is required to win with big data. They argue that assuming data scientists as the single most important role in big data is a misleading myth. Business-oriented roles must be considered, including business analysts, system managers and program personnel (De Mauro et al., 2016). In an HEI context, we assume the role of big data performers involves data scientists and other IT staff who could be system managers or academics. Thus, we hypothesise that:

H2: Big data analytic performers positively affect BDTs, including storing, analysing, and visualising.

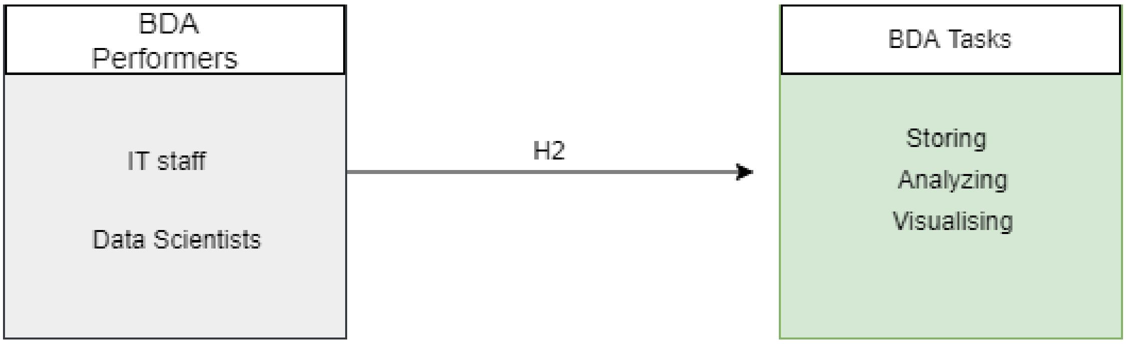

Figure 3.12. Hypothesis 2

3.6.3. Organisational Culture and BDA Systems Quality

Various studies have pointed out how important organisational culture is in determining how businesses react to new technologies (Westrum, 2004) and how productively businesses can use technology to accomplish their goals (Dubey et al., 2019). The willingness of businesses to adopt new technology in business process development and automation (BDA) is one indicator of the organisation's culture (Sam and Chatwin 2019). Moreover, a performance-oriented BDA culture is facilitated by the organisation's emphasis on flexibility (Iivari & Huisman 2017). In order to take advantage of the possibilities presented by big data, it is essential to successfully implement a culture shift towards making decisions based on evidence (Alharthi et al., 2017). The speed with which technology evolves means businesses need to be adaptable to reap the benefits of this phenomenon. Perspectives from developing nations such as Saudi Arabia suggest that system aspects like information security have become integral to organisational culture (Al-umaran 2015). Not only that, but both big data and BDA are always evolving, which means that embracing the latest and greatest technologies in BDA may include new necessities in terms of infrastructure as well as more advanced capabilities. (Alalawneh &Alkhatib 2020).

Moreover, various studies have emphasised on the impact of organisational culture on systems for sustainability (Dubey et al. (2017), system success (Romi Ismail, 2011), and the adoption and implementation of internet-based technologies (Dasgupta & Gupta, 2019). Other studies have focused on specific technologies like KMS (Alattas 2016) and data warehouse adoption (Dasgupta &Gupta 2019). Overall, an adaptive organisational culture enhances the organisation's effort towards using internet technologies (Dasgupta & Gupta, 2019). In BDA, organisations with a flexible cultural orientation are more likely to use BDA in collaborative tasks than control-oriented organisations (Dubey et al., 2019).

Romi Ismail (2011) proposed that organisational culture could influence system, service, and information quality; however, this proposition was never tested. Concerning system quality as a critical element of big data environments, Lin & Luo (2021) argue that information security diagnosing, solving, and performing behaviours are shaped by organisational cultures through individual sensemaking processes. Also, privacy is a key concern in big data environments, which could be managed by the organisation's commitment to best practices for creating rules and processes, managing sensitive information about customers, and observing legislation (Alharthi et al., 2017). Evidence suggests that information system success is influenced by corporate culture (Bradley et al., 2006). Notably, IT planning and system quality are greater in firms with entrepreneurial cultures than in formal ones (Bradley et al., 2006). While a few studies have looked at the effect of organisational culture and information systems in different contexts, especially the new technology sphere, it is hardly unexpected that studies on culture have concentrated in selected countries. We hypothesise that:

H3: Organisational culture to accept and adapt technological improvements has a positive effect on big data system quality.

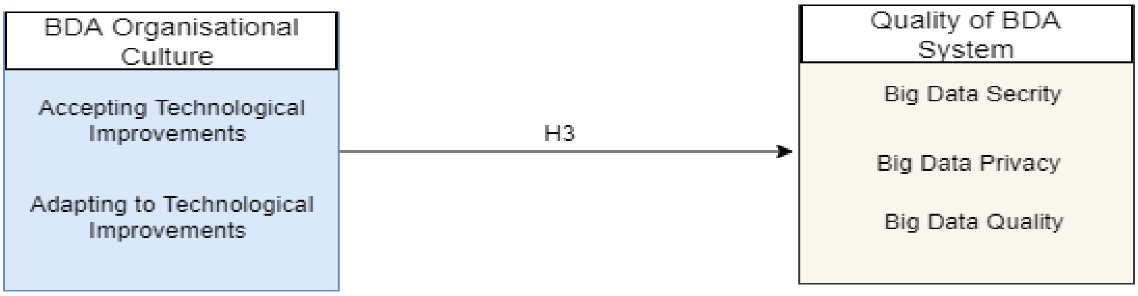

Figure 3.13. Hypothesis 3

3.6.4. Organisational Culture and BDA performers

Organisational culture denotes key competencies that encourage harmony between organisational and personal principles and is linked with organisational success (Azeem et al. 2021). Organisational culture could help transform processes by aligning with employee innovativeness in the IT industry, particularly the adaptive culture (Vinh The et al., 2019). Accepting and adapting to new technologies was defined by Dasgupta &Gupta (2019) as the degree to which an organisation is adaptable and consistent and how it empowers people to accept and adapt new technologies to accomplish the organisation's goals. Besides, cultural values within organisations have traditionally been seen as a long-term base of the organisation, enabling organisational staff members to identify changes and adjustments inside that particular organisation (Costanza et al. 2016). While organisational culture cannot be completely altered but is adapted. Organisations may leverage their existing culture and capabilities to meet necessary changes and promote innovative strategies in formal and informal forms. Cultural changes enable the organisation to cultivate a digital culture among employees at different levels. In general, organisations can more successfully accomplish their goals when they have a technology-focused culture (Jarrah et al., 2020).

Dasgupta &Gupta (2019) highlighted the significance of culture in the adoption and utilisation of information technologies. Besides, an individual's ability to carry out everyday duties is influenced by organisational cultures. Nonetheless, not every culture is equally represented in the organisation; individual and organisational culture may significantly impact task-oriented behaviour, proficiency, and practices. Organisational culture influences people's sensemaking in BDA and shapes information security behaviours (Lin & Luo, 2021). Organisational culture informs the acquisition of IT infrastructure and information systems development and motivates management and non-management staff (Claver et al., 2001). In the era of BDA, organisational culture has become imperative to increasingly evolving new technologies. Saudi Arabian universities , for example, are one of the quickly expanding contexts that needs a culture to help IT personnel and data scientists accept and adapt to new BDA technology advancements. Thus, we hypothesise that:

H4: Organisational culture of accepting and adapting to BDA technological improvements has a positive effect on big data analytic performers, including IT academic staff, IT non-academic staff, and data scientists.

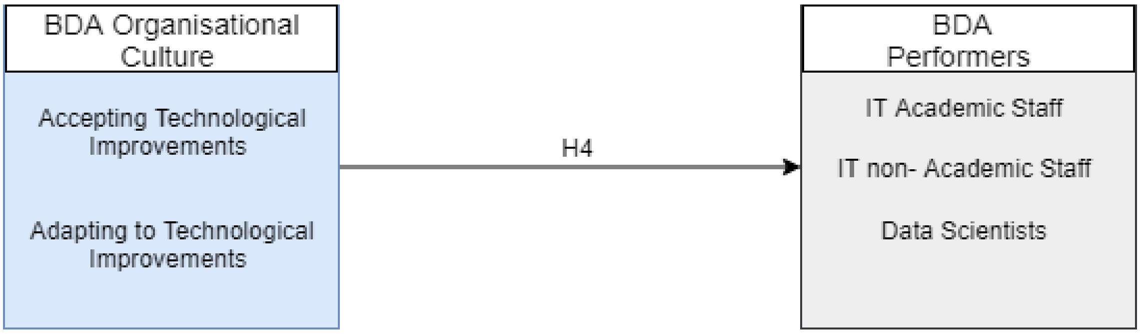

Figure 3.14 **Hypothesis 4**

3.6.5. Organisational Culture and BDA Tasks

Before we can begin to comprehend how organisational culture influence big data tasks, we need to have a deeper understanding of the intangible factors of organisational culture, such as organisational learning in accepting and adapting to big data analytics technologies (Mikalef, Pappas, Krogstie, & Giannakos, 2017). As defined by Gupta &George (2016), organisational culture is a process by which companies investigate and store information for later use, as well as a method by which firms communicate and apply knowledge. BD is a data-driven culture is a crucial component within organisations that encourage top management to implement big data tasks such as storing analysing, and visualising to improve strategic decision-making. The senior management of the company makes decisions and creates strategies to achieve the goals of big data tasks as a result of this data-driven culture. Employees are beginning to recognise data's essential function in their firms. Similarly, an analytical, data-oriented corporate culture is, first and foremost, necessary for successful BDA performance. As a result, analytics are backed by upper-level management, made widely available across the organisation, and trusted by employees at all levels. The data itself, which may then be analysed, is also crucial. All of the company's departments must contribute high-quality data for it to be integrated (Popovič et al., 2018). In order to carry out BDA, one must have access to the right resources as well as knowledgeable and capable staff. In addition, businesses need to strike a balance between gut instinct and data-driven analysis when making important decisions that allow them to gain a competitive edge. Consequences like these include reduced expenses and increase business values(Fernando & Engel, 2018)

According to Devalle, & Couturier (2018), change management and re-alignment of existing organisational culture are required across all levels to reap full value from big data analytics. In this aspect, an organisation's tangible, human, and intangible resources are vital to exploit big data's benefits. Tangible resources include data and technology. Organisational learning and data-driven culture form intangible resources of an organisation, whereas human talents comprise management and technical skills (Gupta & George, 2016b)

Since big data investment aims to strengthen the organisation's ability to make better decisions, Sjusdal & Lunde (2019) suggest a link between organisational culture and big data analytics. They argued that organisational culture positively impacts big data analytics capabilities, which positively impacts firm performance. In a firm, the link between big data managers and functional managers is vital for building big data capabilities, but this relationship is contingent upon mutual trust, collaboration, and communication (Gupta & George, 2016). The people involved must be able to interpret and assess big data insights for the meaningful impact of culture on BD tasks. Overall, organisational structures and values influence task organisation and goals (Marcoulides & Heck, 1993).

Thus we hypothesised it as

H5: Organisational culture to accept and adapt technological improvements positively affects storing, analysing, and visualising big data.

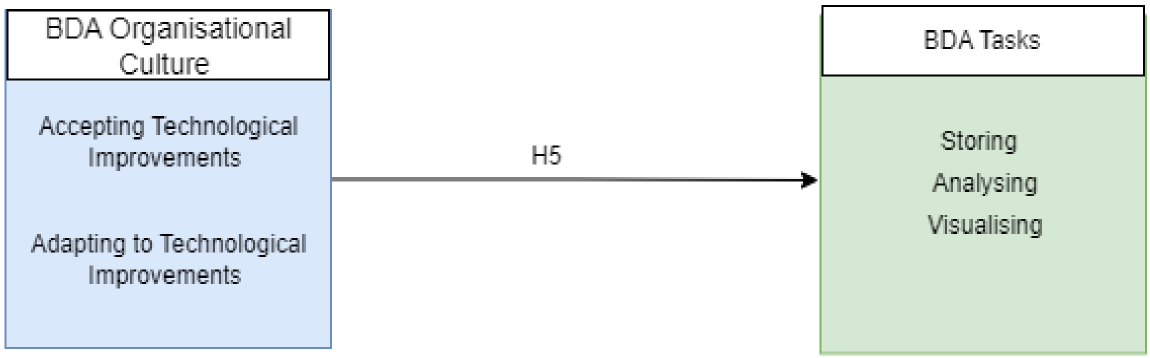

Figure 3.15 **Hypothesis 5**

3.6.6. Organisational Culture and Decision Making

The majority of the literature discusses numerous cultural issues associated with BD adoption. The various challenges are classified according to the dimensions of organisational culture. In today's rapidly changeable market and the growth of new advanced technology, such as big data, organisations are being forced to improve their agility and adapt to new big data technological improvements that lead to improve the decisions of executives. . These challenges are due to the lack of organisational culture that allows the firms to compete with the rapidly changing technologies of BDA in improving the decision-making (Côrte-Real et al., 2019). Lunde et al. (2019) claimed that despite having the right technology, firms are still unable to fully utilise big data capabilities because of unsupportive organisational culture; as a result, culture either hinders or improves the potential for big data benefits. 2019 (Lunde et al.) Decisions at the strategic, structural, and management levels are all impacted by organisational culture (Attar 2020). Making decisions are shaped by how individuals understand how they understand the perspectives and ideologies of in light of the organisation's shared values, customs, and beliefs. Data-driven culture and of intangible resource that should be appreciated and put into practise in order to acquire a competitive edge (Gupta & George, 2016). Data-driven culture can be used to encourage the growth, upper management must deliberate over and settle on an appropriate approach, then shape the organisational structure to accommodate the group's shared values and norms. Business analytics and big data are more likely to be used successfully in an organisation where leadership and employees share an appreciation for the significance of data (Lunde et al., 2019).

The inability to make timely and strategic decisions impacts every aspect of the organisation and its relationship with others (Ax & Greve 2017). Organisational culture impacts how personnel react and implement decisions, influencing the effectiveness of decisions and resulting actions (IvyPanda, 2019). Some organisations involve their employees in strategic decision-making processes, while others do not; but those who do have better possibilities for effective outcomes. Dasgupta & Gupta (2019) pointed out how adopting new information systems should be guided by the organisation's principles and beliefs. They emphasised the need of taking into account individual values of different cultures while researching the intersection of IT and management.

Although all cultures may not become equally prevalent in the workplace, transnational, national, and professional organisational cultures are likely to impact task performance and decision-making. For example, in the Arab corporate culture, decision-making revolves around consultative authority, which is shaped by authoritarianism, collectivism, and centralisation culture (Hammoud, 2011). Organisational culture plays a crucial role in developing information systems and motivating decision-makers such as senior IT managers (Alharthi et al., 2017; Jalal, 2017; Thirathon et al., 2017). While BDA capabilities promote firm performance, organisational culture is an imperative mechanism between the firm’s internal analytical knowledge and BDA (Upadhyay & Kumar, 2020). For instance, small organisations tend to follow an analytic culture more than large organisations, and therefore the former are more likely to base their decisions on BDA (Thirathon et al., 2017). Changing a firm’s decision-making culture could improve its analytics and big data use (Frisk & Bannister, 2017). The role of organisational culture in improving management and institutional performance in higher education is undoubted. Thus, we hypothesised it as

H6: Organisational culture of accepting and adapting technological improvements positively affects decision-making.

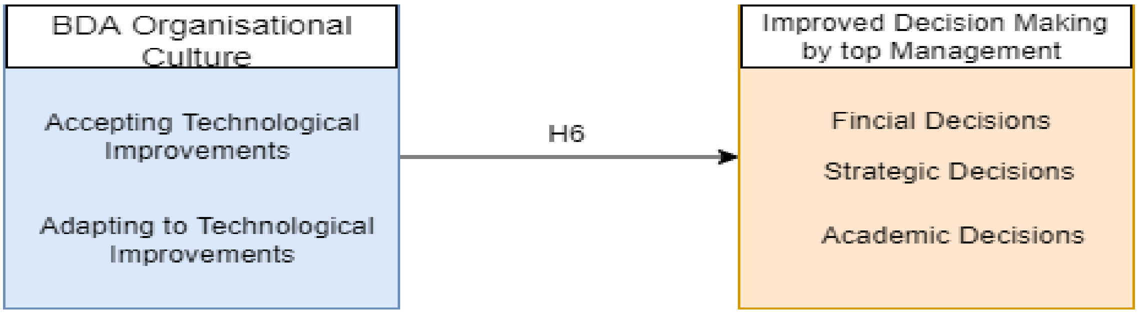

Figure 3.16. Hypothesis 6

3.6.7. BDA Organisational Culture and Enhancing University Performance

There are two decades of evidence to explain the role of organisational culture in firm performance (Lim, 1995; Marcoulides & Heck, 1993; Martínez-Caro et al., 2020; Ng & Kee, 2013). To extend this knowledge, researchers investigate the question in different sectors and under different technology environments. Ji-fan Ren et al. (2017) discovered that the global economy might benefit greatly from the collection, storage, and mining of big data for insights, which in turn boosts business and government efficiency and competitiveness while also providing consumers with a significant benefit which leads to enhance organisation performance (Ashraf & Verner, 2017). Likewise, McAfee and Brynjolfsson (2012) demonstrated how Big Data Analytics might revolutionise the decision-making process by boosting transparency into business operations and enhancing performance. Similarly, Ji-fan Ren et al. (2017) proposed the BDA capabilities model to evaluate the success related to financial performance) of a firm and increase its enterprise value compared to process-oriented dynamic capabilities (PODCs); firm performance is influenced by BDA capability, which affects operational outcomes. (Wamba et al., 2017). Using BDA, a firm can boost its productivity and competitiveness, as stated by Gupta and George (2016). Adopting a data-driven culture can forecast significant financial performance, according to Ji-study fan's (Elia et al., 2021). Resultantly, businesses must promote a data-driven culture for the purpose of increasing data usage in making decisions. Because employees at all levels of an organisation are responsible for making decisions, it's essential to instil a culture of making decisions (DDDM) throughout the entire organisation to ensure that all employees, regardless of their position, are able to make sound judgments supported by concrete evidence. Previous studies suggests that the culture of making decisions is crucial to the success of higher education sectors. Those in control of higher education institutions (HEIs) who are adept in statistical analysis and decision making are more likely to use data as a central component in the context of HEIs' evaluation processes and regulatory compliance. These adapation of organisational culture could improve the performance of higher edcuation institutions (Aseeri & Kang, 2022; Ashaari et al., 2021).

Over the past few years, various educational institutions have created technology capabilities and solutions to enhance the quality of their services, but it is yet unknown whether these efforts will result in the desired firm performance. The impact of organisational culture on increasing academic productivity through remote workers and virtualisation technology was acknowledged by Pawirosumarto et al. (2017). They observed that organisational culture positively impacted the adoption of virtualisation technologies among remote workers in Iranian universities. Virtualisation technology can be used as a crucial resource for maximising efficiency in the university. Wahjudi et al. (2016) investigated organisational culture and the performance of manufacturing firms. They noted that only individualism and uncertainty avoidance cultures affect firm performance. In other cases, organisational culture acts as a mechanism that reinforces performance in digital technological environments (Martínez-Caro et al., 2020), strategic agility (Arokodare et al., 2019), and high-performance work systems. Thus, we hypothesised that,

H7: Organisational culture to accept and adapt technological improvements positively affects university performance.

Figure 3.17 **Hypothesis 7**

3.6.8. System Quality and Improved Decision Making

Due to the fact of the velocity with which big data is generated, big data analytics is more critical than ever (Elgendy &Elragal 2016). Decisions made by today's top executives are increasingly consistent. This enhances the performance of the business (Adrian et al., 2018). The effectiveness of a person's decision-making is influenced by the system and information they access (Aldholay et al. (2018). A good quality system is user-friendly, easy to adapt, easy to attach, and attractive to use, while good information quality relates to storing, analysing, and visualising analysed data attractive manner for improving the decisions.

The quality of a BDA system revolves around common characteristics such as reliability, adaptability, accessibility, and privacy; information quality relates to completeness, accuracy, currency, and format (Ji-fan Ren et al. 2017). System quality is crucial in handling data volume, velocity, and variety (Brynjolfsson &McAfee 2012). Besides, system quality enables transaction, transformational, and strategic value for the firm (Ji-fan Ren et al. 2017). Evidence in developing countries suggests that system quality affects transformational leadership, which inherently affects system use and firm performance (Aldholay et al., 2018).

BDA system quality focuses on building a secure system (Jung 2017). Information security contributes to effective decision-making and supports the organisation's planning and execution procedures (Cavallo et al., 2019). Due to big data velocity, firms are responsible for managing the amount of big data stored (Wood & Member, 2019). The velocity of big data raises concerns about big data quality (BDQ), a critical success factor for an organisation's performance (Janssen et al. 2017). Also, data quality allows business leaders to make better decisions faster (Trieu Van-Hau Thi &Arif (2018). (Janssen et al. 2017) argue that big data quality is not only on the sources stored data but also on system's ability to produce good quality data to improve the quality of decisions of top management.

When considering big data, one might think of a large amount of data and its wide diversity. However, as big data continues to expand in popularity, concerns about data quality, privacy, and security will increase. Some scholars contend that big data could negatively influence new technology (Jordan Columba 2017). Besides, Cryptography is a useful mechanism for maintaining privacy. Some scientists believe that public data and privacy protection can be provided by applying a bitmap encryption scheme to the huge amount of data already being collected. With big data analytics, privacy issues arise. Personal data collection has increased throughout the years, according to (Jones 2021). It is harder to catch up with technological changes, so collecting personal data is increasingly possible. A large grey area that the law cannot solve remains, and that privacy. Many questions have remained unanswered. How much data is obtained? Who has access to it? And who might be tracked? Yoon et al. (2015) argued that information should be processed if it is encrypted, and if alterations are detected, then controlled with PigLatin for encrypted data. According to Stephen et al. (2019), system access control, restricting access to individuals who are actual system users, is an established way to preserve user privacy. The Big Data system could use an integration framework for access management (Jordan Columba 2017). Thus, we hypothesised that,

H8: The quality of big data systems, including big data security, privacy, and quality, positively influence top management decision-making.

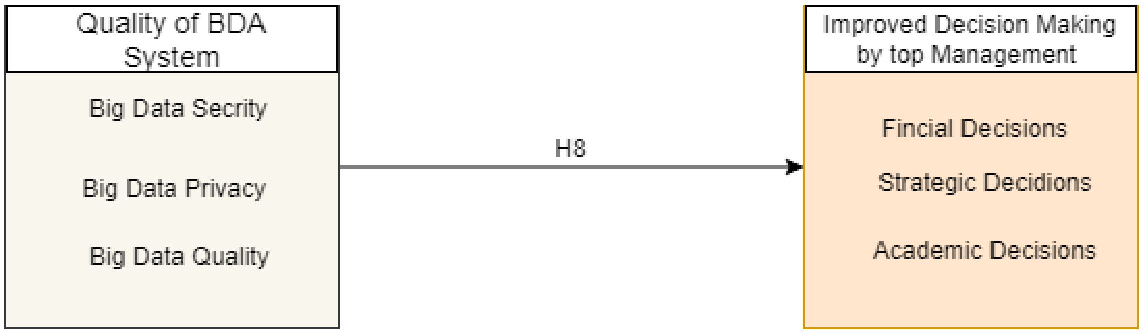

Figure 3.18 Hypothesis 8

3.6.9. Big Data Tasks and Decision Making

To make sensible decisions in the face of uncertainty, it is essential to collect and analyse relevant data and visualise those analysed data for better decisions (Intezari & Gressel, 2017). The best action plan can be developed with sufficient evidence, precise data, and careful analysis. There should be more research into the effectiveness of BDA in the decision-making of top management in higher education. Due to the fact that there is a dearth of studies on the topic to date (Janssen et al., 2018).

Various sources and formats are used to collect data. Securing big health data technologies is essential from the beginning of its lifecycle from a safety point of view. To this end, it is crucial that reliable sources be used to compile data, that individuals' privacy is preserved (no attempt should be made to identify specific patients in the system), and that this stage be safeguarded and protected (Hariri et al., 2019). All data and information systems need to be safeguarded against unauthorised access, disclosure, modification, duplication, diversion, destruction, loss, abuse, and theft, which necessitates the implementation of some advanced security measures (Raut et al., 2021).

A critical task in big data is storing big data, which involves various data types collected from diverse sources and stored in a variety of formats. For instance, Hbase, NoSQL, Gluster, High Density File System (HDFS), and Google File System (GFS) are among the effective tools for storing massive quantities of data. The storage phase of big data management requires the completion of activities, including data consolidation, data replication, and data archiving, all of which involve multitasking in order to store enormous volumes of data effectively (2016 Siddiqa et al.).

Data analysis, which entails using analytical approaches to the data to make inferences and conclusions, is the second critical step in big data. The storage phase of big data management requires the completion of activities, including data consolidation, data replication, and data archiving, all of which involve multitasking in order to store enormous volumes of data effectively. Big data collection and analysis enhance decision-making and adds value to businesses (Saggi &Jain 2018). Likewise, Wamba et al. (2016), the majority of companies have started using BDA to find the perceptions that could help them fully comprehend business market factors and make effective and timely corporate decisions.

Data visualisation, which includes using big data to improve the effectiveness of decisions, is the last phase of big data analytics jobs. Besides, visualising analysed data to decision-makers will easy decision-making processes and improve the quality of decisions being made. (Thirathon et al. 2017). Truc Nguyen (2017) stated that a lack of data-driven culture in higher education is concerning as such institutions are among the organisations that could benefit BDA. Thus, we united the three big data tasks as the main activities for improving decision-making, we hypothesised that:

H7: Storing, Analysing, and visualising big data will positively affect top management decision-making.

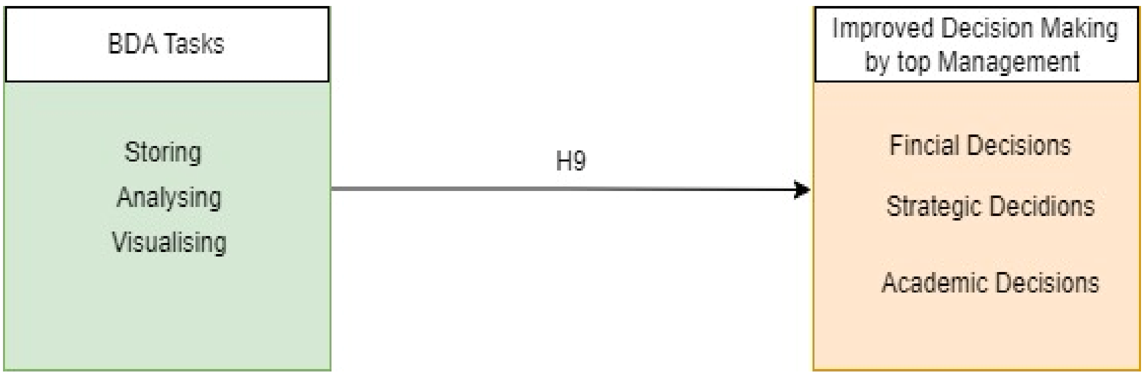

Figure 3.19 Hypothesis 9

3.6.10. Decision-Making and Organisation performance

The overall strategy of a company, which may include but is not limited to profit maximisation, client retention, and corporate objectives, depends on value creation. BDA has been viewed as a capability that can add value (Chen et al., 2015; Saggi & Jain, 2018; Zeng & Glaister, 2018). BDA value directions have been linked to advantages for businesses like revenue growth, increased productivity, and cost savings (Elia et al., 2020). BDA is a crucial point of differentiation since it forces companies to act strategically and in the direction of their rivals. BDA thereby helps businesses save money and increases the company income by 8%. (Wamba et al., 2017) The literature also offers a case study of a target business that uses BDA to track consumer purchase behaviour and predict future buying trends through membership programmes, value creation, and market research (Wamba et al. 2018).

The BD system offers decision-support capabilities and guides decision-makers to the right course of action (Elia et al., 2020). With accurate data, effective decisions can be derived, and as a result, the ability to make effective decisions translates into organisation performance (Trieu et al., 2018). Similarly, it's also important to understand that if the decision is founded on facts or assumptions, it will most likely result in effective decisions. On the other hand, if the analysed data is erroneous, it might be a challenge for the decision-makers to use, which may negatively affect the overall performance of the organisations (Trieu et al., 2018).

Although big data analytics is universally acknowledged as critical for increasing corporate competition and improving business performance, a recent Deloitte survey revealed that big data analytics is still not frequently used in many nations and regions (Müller et al., 2018). It is timely to investigate whether and how big data analytics creates value and competitive advantages in different economies and sectors. Also, existing literature shows varied views of significance BDA for firm performance. To explore whether big data-driven decisions improve institutional performance, specifically in higher education sectors, we hypothesised that

H10: Financial, strategic, and academic decisions of top management, all taken together, have a positive effect on enhancing university performance, i.e., creating business values and academic outcomes.

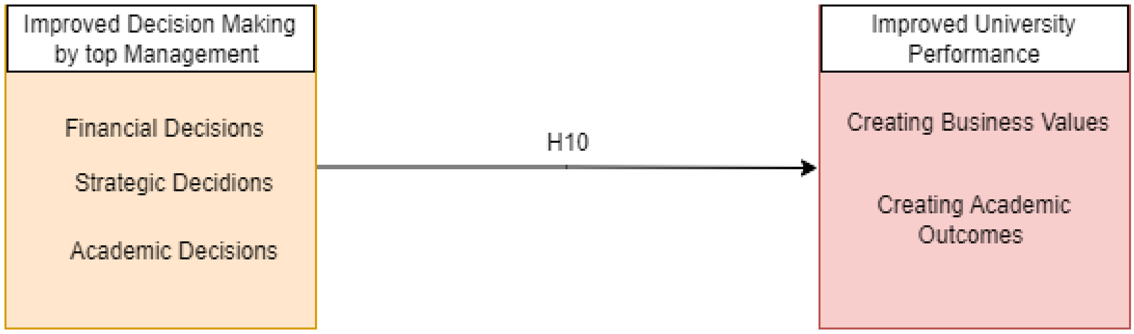

Figure 3.20 Hypothesis 10

3.6.11. Big Data Performance and Improving the Decision Making

In the past, employees' primary means of participation in workplace decisions and processes was through their union representative, supported by a trade union. However, evidence from trade unions and their members suggests that employee involvement today also incorporates employees' ability to contact directly with leaders and voice their concerns about workplace conditions (Korsgaard et al., 2019). Besides, the author also highlights the significance of a relationship between employee engagement and innovation, as employees are more likely to demonstrate "innovative ideas and new insights," which increases the likelihood of innovation when given opportunities to voice their opinions to leaders and take part in decision-making processes. Similarly, Philip (2020) argued that employees perform better and show greater initiative, knowledge, and excitement when they are given a voice in organisational matters. As a result, productivity rises, and the business expands. Participating actively in making decisions has a good impact on the final outcome.

and benefits the productivity and enjoyment of employees. According to research, if the level of inclusive leadership reaches the highest level, the perception of exclusion will be reduced; however, it may be difficult for leaders to incorporate subordinates' opinions and perspectives in decision-making processes due to "very fundamentally different options from employees" (Xiaotao et al., 2017). However, a high level of inclusive leadership may reduce employee task performance. In this regard, the authors advise maintaining a moderate level of inclusive leadership to include employees' perspectives in decision-making and improve task performance.

Since decision-making is the root of the administrative process and the fundamental means by which the organisation's goals can be achieved, providing employees with opportunities to express their thoughts, ideas, and proposals can minimise conflict and enhance motivation (Zaqout et al., 2018). The climate in the internal work environment influences many decisions, behaviour, and attitudes towards the organisation. Besides, the surrounding environment influences the individual's behaviour within the organisation, effectiveness and efficiency of individual and collective performance (FarajAllah et al., 2018).

Universities are a great example of an institution that requires the involvement of administrative staff in decision-making to enhance employee performance and enable them to fulfil their essential role within the university (Agasisti & Bowers, 2017). IT staff and data scientists are great examples of the staff that could involve in executives' decisions. In light of the role of big data performers in educational sectors, we propose forming a more robust professional role for data scientists applied to education sectors. This can preserve and reinforce a beneficial data-driven approach to decision-making in the education sector. We believe creating a job for a data scientist who can serve as a "bridge" between data analysts and educational managers will be most beneficial in this area (Agasisti & Bowers, 2017). Besides, the results of the empirical analysis can be used to realise "Action(s)", such as designing corrective interventions, creating new (or modified) curricula, developing early warning systems, stopping phenomena that harm student achievement, encouraging the development of creative educational strategies by (groups of) teachers (Shrestha et al., 2019). Likewise, big data performers are referred to the skilled people who can deal with complex big data and have the knowledge of mathematics, programming, machine learning algorithms, and big data analytics tools that assist them in analysing those big data for enhancing decisions (Engelsrud, 2017). Thus, the study hypothesized:

H11: Big Data Performers BDP positively influence the decision-making by top management in Saudi higher education.

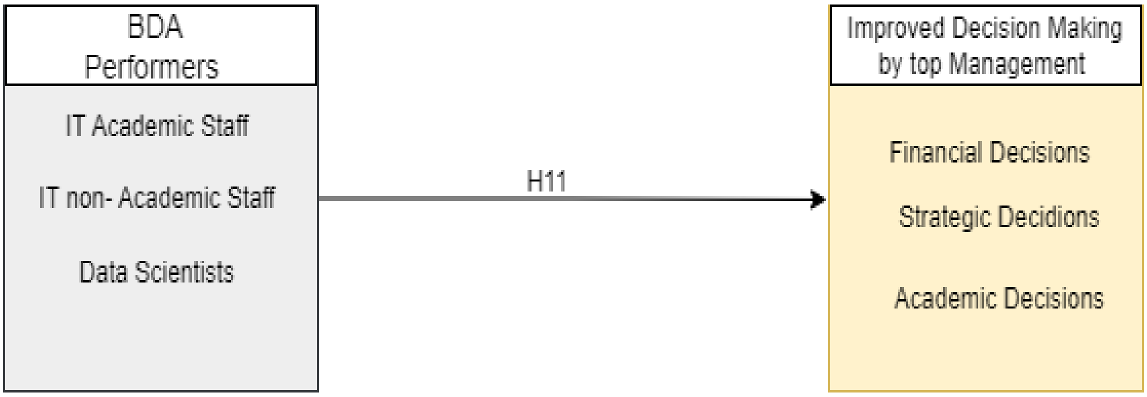

Figure 3.21. Hypothesis 11

3.7. Chapter Summary

Acceptance Model (TAM), the root of TAM mode such as the theory of reasoned action the theory of planned behaviour (TPB), The Unified Theory were among the theories that were extensively used in this chapter's discussion of information systems research. Alternative theories that might provide a more solid framework for this research were identified, along with a description of the potential drawbacks of the aforementioned theories. The sociotechnical theory and the DeLone & McLean information system success model are among the theories that are selected for further investigation in this study. These theories allowed us to combine the social and technical subsystems of the big data system. The technical subsystem's conceptualisation and operationalisation depended heavily on the Sociotechnical theory and information system success model. Our study model and research hypotheses were then provided in the chapter. The link between the factors identified in the research model is provided under hypothesis development. Research methodologies are addressed in Chapter4.

CHAPTER 4

Research Methodology

4.1. Introduction

This chapter focuses on methods employed for this study to determine the impact of social and technical factors that influence the implementation of BDA toward improving decision-making, which improves the overall university performance of Saudi Higher Education. To begin, the research paradigm is defined. Research approaches are then discussed, along with the design of this study. Then, the population and sample are presented, as well as the data collection and analysis procedures for quantitative and qualitative followed by ethical consideration of the current study. Finally, the chapter ends with a summary. In the following paragraph the author will define the terms and definitions related to this chapter. First the author will begin with the Ontology, Epistemology, and Methodology.

Ontology is associated with existential philosophy and the different views and positions on what is and is not true (Willis, 2012a; Scotland, 2012; Willis, 2012b). Ontology is described by Lincoln & Guba (2013.p.108) as "the ideologies and hypotheses that researchers use in their query for new information. Materialism, idealism, or philosophical subjectivism are also possible ontological views. Only physical objects are true according to a materialist ontological belief. As a result, they disbelieve in non-physical entities such as the soul. According to idealists, "truth is conceptual and metaphysical in nature rather than material in nature (Willis 2012). Finally, philosophical subjectivists asserted that truth is formed solely by experience (what we feel with our senses); therefore, there is no other reality but the one we construct in our minds ; what is the origin and shape of life are ontological issues. Besides the definitions discussed above '(Hirschheim 1985,p.13) defined ontology as 'the nature of the world around us; in particular, the reality that scientists choose to address. Crotty (1998) believes that ontological issues emerge with epistemology; therefore, one may not necessarily need to develop their research boundary to specify ontology claims.

Epistemology The term "epistemology" derives from the Greek language episteme, meaning intelligence epistemology is described as the intellectual method. The link between our knowledge and our perceptions (Willis 2012a). The truths that we as scholars discover and believe. Several epistemological issues include 'What is knowledge?' and 'How can I learn knowledge? What is the essence of the bond between the knower and would-be knower, and what is knowable? (Willis 2012a; Lincoln & Guba 2009). As well as 'what is the researcher's relationship to the subject of the research? (Guba, E. G., & Lincoln 1994, p.103).

Methodology Can be defined as the process of acquiring information (Divers 1984). Besides, Ellen (1984) described methodology as a systematic examination of the concepts that guide sociological exploration, the forms in which theory is applied, and the method for data collection. Likewise, the methodology is 'the mechanism by which we pursue new information, the guiding principles that govern our investigation, and how the enquiry should continue Lincoln et al. (2011, p. 104).'Among the methodological issues are how can the inquirer uncover what they believe is identifiable?" Lincoln & Guba (2011.p.108). Paradigms, in general, were discussed in previous paragraphs. The next section will discuss the paradigms: Positivism, critical theory, and interpretivism.

4.2. Research Paradigms

Meadows (2009) defines research as "a theoretical and systematic exploration for relevant knowledge on a particular subject. Besides, Tuchman (2019) described the research as the method of identifying a solution to an issue through an in-depth examination and review of the contextual aspects. Nevertheless, the phrase "research paradigm" is a framework for organising and carrying out research. In addition, it is a shared conceptual framework in which the practices may be implemented successfully; it also refers to distinct approaches to research (Willis 2012). Similarly, the three theories of positivist, critical theory and interpretivst are the most often addressed in academia. (Neuman, 2007). Based on the study of McChesney and Aldridge (2019), paradigms are described by some basic assumptions about ontology, epistemology, and methodology. The assumptions include an extensive understanding of how The assumptions give a comprehensive understanding of how knowledge is seen, how we identify ourselves in relation to the knowledge, and how information is discovered. (Scotland 2012). The next sections will discuss those paradigms (ontology, epistemology, and methodology).

4.2.1. Post positivism

A major principle of positivism is that the scientific method is the dominant or exclusive method for determining the facts about the universe. Positivism, or empiricism, believes that we will uncover universals of human nature if we observe them logically and critically in a well-controlled environment (Willis 2012a). Moreover, positivism and postpositivism constitute the majority of natural science studies. In the nineteenth and twentieth decades, they have served as a base for the human sciences. Smith (1989) identifies Auguste Comte, a French economist, with introducing positivism into the social sciences. According to the post-positivism theoretical point of view, We acknowledge that we cannot make a "positive" claim of knowledge while studying human behaviour and activities.'(Creswell 2003, p.7), such as social networking actions within the organisation related to big data analytics. The attention is to explore social and technical subsystem factors by reducing the wide range of varying ideas into discrete sets of testable ideas through research questions (Creswell 2003). Thus, the study will begin by developing hypotheses, and quantitative data was collected to support or reject the hypotheses. Then we made necessary revisions, including integrating our framework's emerging constructs. The framework's validation then takes place through qualitative data collection to refine and confirm the causal mechanism represented by the framework of BDA in Saudi higher education.

Although post-positivism remains the most widely accepted social sciences theory, two significant equivalents have arisen in the last 50 years: interpretivism and critical theory. These alternative paradigms will be discussed in the next sections.

4.2.2. Interpretivism

Interpretivism believes that human society is not measurable by scientific approaches. In other words, human behaviour cannot be measured using the same method for measuring other sciences such as Chemistry or Physics (Ponterotto 2005). Besides, Willis (2012) states that interpretivism is typically concerned with comprehending a given meaning, and the interpretive paradigm's central assumption is socially created. Therefore, interpretivist scholars pursue approaches that allow them to understand comprehensively. As a result, interpretivists do not support approaches with impartial or quantitative detail. Rather than that, interpretivists see the world from a 'set of human eyes' and select individuals who "use their views of facts" to encompass the worldview (McQueen 2002, p.55). Subsequently, Willis (2007) also mentions that interpretivists prefer observational approaches, including case studies and ethnography. However, as Willis explains, qualitative methods often provide detailed reports that allow interpretivists to understand contexts truly. Congruent with Willis's assertions, Trudgill (2001) insists that interpretivists generally favour qualitative approaches since the interpretivist theory portrays a world in which truth is socially created, complicated, and constantly evolving.

Similarly, Nguyen et al., (2015) identify that interpretivism is a methodological trend in science that favours observational data collection methods. The interpretivist theory and qualitative methods are inextricably linked since one is a methodological approach, and the other is a technique for data collection. Investigators who use an interpretivist paradigm and relational approaches often pursue evidence from individuals' views and perspectives rather than relying on statistical numbers.

4.2.3. Critical Theory

In the 1920s, Critical theory was founded at the institution of social science at the University of Frankfurt. Social theory is considered as a map or reference to the social realm. As research proceeds, it is more about helping one design questions and methods for understanding the environment than informing our perception of the world. A critical social theory is particularly concerned with questions of power and justice and the various social structures that form the social system (Mclaren 2011). In view of this, the critical theory follows a political method to understand and improve the environment by posing philosophical and political questions such as 'Does society remain in its current form? Why isn't our community more egalitarian?' rather than scientific questions such as 'How does civilisation operate?' Critical thinkers are concerned with critiquing and transforming society through social change. Critical theory presupposes that reality is influenced by race, racial, technological, financial, political, and gender influences (Guba, E. G., & Lincoln 199). Thus, a critical thinker approaches studies with a change agenda in mind, aiming to change the subjects' lives, the world they serve or live in, and the researcher's own (Creswell, 2009). A critical theory-based analysis begins with a central social problem such as 'empowerment, injustice, coercion, dominance, suppression, or alienation" (Creswell, 2009, p. 207). This method of study is collaborative, with participants contributing to the creation of questions, gathering and analysing data, and benefiting from the research's outcome (Creswell, 2009). Thus, analytical theorists assist individuals in overcoming 'humanly created and collectively replicated limits' (Martnez-Alemán, Pusser, & Bensimon, 2015, p. 9). Figure 4.1 illustrates the study design.

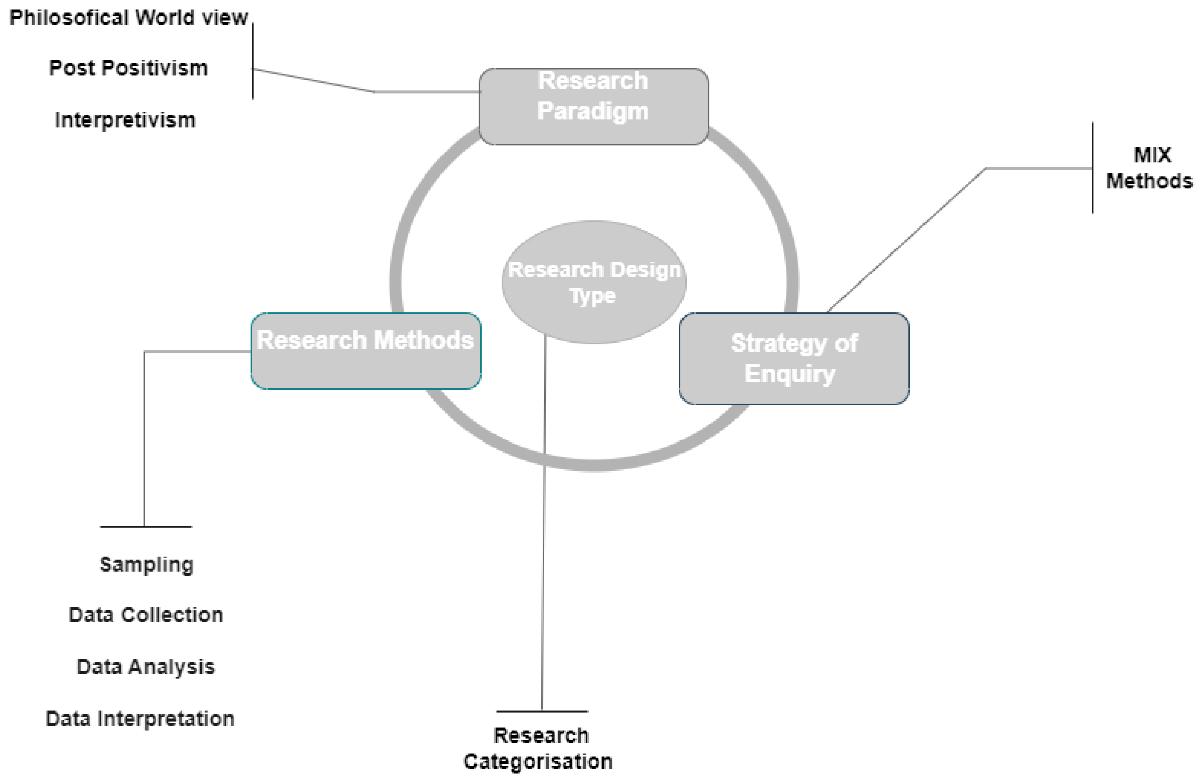

Figure 4.1. **Research Design**

4.3. Research Paradigm of this Study

Undeniably, research paradigms guide researchers in how to perform a study. A paradigm analyses social processes from which specific explanations and interpretations can be gained (Saunders et al. 2019). Positivism, critical theory, and interpretivism are the classifications of science paradigms (Willis 2012a). However, according to scholars, these classifications and naming conventions differ (Meyer et al., 2007). In this research, we selected Post-positivism for the quantitative methods and interpretivism for the qualitative methods. These two paradigms are discussed in the next sections.

4.3.1. Post-positivism

Post-positivism is a school of thought that focuses on empirical evidence and the scientific method; post-positivists have broadened their focus to include data science (Sui, 1994). Post-positivism is the idea that the scientific method is a valid and reliable way to gain knowledge. It is contrasted with earlier forms of positivism, which focused on objectivity and truth rather than understanding human behaviour. Post-positivists believe that science should be used to understand human behaviour instead of simply explaining it (Henderson, 2011). It is a philosophy that emphasises the importance of questioning and evaluating what you think rather than accepting what authority figures are. Post-positivists also believe there are no objective truths about how the world works; we all have our own subjective experiences and interpretations of those experiences. In higher education, post-positivist assumptions have been used for decades to shape how students are educated. In order for students to succeed in their educational pursuits, they must first have a firm grasp of the subject matter. Post-positivist assumptions believe learners can make sense of their learning experiences and understand how their learning activities fit into a larger whole (Henderson, 2011b).

Positivism gives rise to the quantitative methodology. This type of method involves the analysis of quantitative data. Quantitative data is measured and can be used to determine the results of an experiment or an observation. The link between positivism and quantitative research is widely discussed in the literature. Positivism studies the physical world, including human beings and society, "social aspect of BDA". Quantitative research refers to the use of numbers as a tool for describing or measuring phenomena.

The positivist-inclined approach to data analysis is often referred to as "quantitative analysis" because it seeks large datasets. This approach can be used to gain broader insights into a topic. The positivist approach to doing research seeks to gain insight from data rather than subjective observations. This is a common practice in the field of economics and finance, where larger datasets are sought to gain broader insights into the economy and markets (Sheppard, 2017).

In view of the above, big data analytics is a subset of post-positivism that focuses on using data to improve organisations' processes and outcomes. Big data analytics helps companies gain insights about their customers' needs, behaviours, and preferences through analytics tools that can identify trends and patterns in large amounts of data. Big data analytics is simply the combination of postpositivism and data science. This means that big data analytics combines empirical evidence with statistical modelling, allowing businesses to collect vast amounts of information about their customers and analyse it to make better decisions (Choi, 2018).

Researchers prefer quantitative research to big data analytics because it is the best way to get a comprehensive picture of a situation. The data comes from a wide variety of sources, and in quantitative research, researchers can combine that data into one comprehensive picture of the situation.

In quantitative research, researchers can combine all their data in one place and analyse it with various statistical tools that allow them to compare specific pieces of information with variables or other pieces of information within the same variable. This allows them to see trends and patterns in the data that would be missed if they only analysed each piece individually.

I applied post-positivist paradigm in my research to measure how BDA social and technical subsystems, particularly BDP, OC, BDS and BDT, influence the decisions being made by top management of Saudi universities. With the objective of finding how BD-driven decision-making influences a university's performance, I used questionnaires for data collection. In addition, I conducted online surveys to explore the views and experiences of current students, faculty members, and administrators about big data analytics, along with a review of related literature, to understand best practices for big data analytics in higher education.

The post-positivist approach helped me grasp how big data analytics' social subsystem affects top management's decision-making and a university's performance. The social subsystem for big data analytics allows for better communication between top management and the university because it helps them understand the needs of each other, which will lead to better decisions. This can be done by having everyone in both groups attend meetings together, so they can see their perspectives presented accurately and discussed in full detail.

4.3.2. Interpretivism

Interpretivism qualitative research can be used to measure and evaluate the quality of the interpretation. Interpretive data analysis is qualitative research that is applied to analyse the data collected from the respondents and other sources. The interpretive approach usually applies a qualitative approach, with the data being collected through methods in-depth interviews and focus groups (Goldkuhl, 2012). Interpretivism research has a number of advantages over other approaches to research, such as quantitative or qualitative approaches. It provides a holistic view of an issue by providing information about the context in which it takes place. This helps researchers to understand the consequences of their actions and policies on those who are affected by them (Nguyen et al., 2015)

The interpretive research approach is related to big data analytics. It is focused on data interpretation rather than its collection and analysis. Interpretivism uses qualitative methods in combination with mixed methods to understand relationships between variables. Interpretivism quantitative research involves using data analysis techniques to explore the meaning of a topic. This can be done by presenting data to participants and asking them to interpret it or by analysing data from an experiment to see its effect on participants' behaviour (Irshaidat, 2019). Qualitative research is more sensitive to human experience than quantitative research. This is because it focuses on how people feel, think, and act in relation to their environment rather than how much data about them are available or what those numbers mean for them. The best way to do this is through qualitative research—the type of research that involves talking to actual people in order to understand their opinions and attitudes about a topic or issue. Qualitative research can be very effective at uncovering why people do what they do, which is critical when making informed decisions about how best to target your audience and message (McLeod, 2015).

My research finds out how the university's performance would change if BD-driven decision-making was introduced at all levels: senior management, faculty members, students, and staff. It finds positive effects on the university's performance if BD-driven decision-making is implemented and shows how it improves the overall quality of education. In this study, I used interpretivism quantitative research to collect data. The data I collected was used to analyse BDA socio-technical system and determine its impact on top management decisions. The results of my research can be used to influence BD-driven decision-making, which improves overall university performance.

4.4. Research Approaches

Applying a research approach for theory development is crucial. These approaches are classified as two reasoning, which are inductive and deductive. Besides, Saunders et al. (2019) highlighted that abductive is. Alternatively, the third reason for the research approach (Kitchin 2014). As you start off by gathering evidence to investigate a phenomenon, you are utilising an inductive approach; in this instance, your data collection is being used to investigate a phenomenon, identifying patterns, and creating a new or modifying an existing theory (Saunders et al. 2019; Günther et al. 2017). Based on Asare (2019) idea, the inductive reasoning approach relies on interpreting data without specific frameworks or structures. It gives data the freedom to tell its own story (Attride-Stirling, 2001). The inductive methodology assisted the researcher in discovering certain previously unknown facets (Abouassar 2017; Alturise 2016; Asare 2019; Bohon 2018; Brierley 2017; Park 2017).

On the other hand, if the researcher begins with theories and concepts (which also take the shape of a conceptual model), you are using deductive reasoning. A deductive reasoning is used if you begin your study with a well-researched hypothesis and develop a research method to test it (Abbasi, Sarker & Chiang 2018). In addition, deductive reasoning, you must first choose an already established framework or context and then use it as the foundation for your reasoning. This approach allows the researcher to understand how results in the current study were linked to previous studies' findings through deductive coding (Asare 2019; Bohon 2018).

Lastly, abductive reasoning is when the researcher collects additional data to create new or alter an existing theory (Vii, April & Chomczyński 2011). In contrast to inductive or deductive reasoning, which analyses the relationship between evidence, process, and theory, abduction examines the interplay between data, method, and theory. As is the case for any exploratory analysis, the process of experimentation involves ideas, hypotheses, and methods of an enquiry being used to guide the process, with data employed to lead the later research and the process of understanding and theoretical progress. Using this method, relevant data sets can be discarded by domain experts, and those which warrant more attention can be highlighted (Halford & Savage 2017). There is a clear distinction between outsourcing our research to computational methods and engaging the tools and data they produce during a sensitive period of questioning by abductive reasoning. From trying to disprove theories to finding out how to organise mountains of data into concrete information divisions, philosophy plays a greater role. Table 4.1 will summarise the three reasoning approaches mentioned above.

Table 4.1. Types of reasoning in research design

	Deduction	**Induction**	**Abduction**
Logic	The conclusion must be true in deductive inference if the premises are valid.	Inductive reasoning employs proven theories to generate assumptions.	The conclusion follows from the known premises
Generalisability	It is from generalised to specific (narrowed).	It is from specific to general.	Generalisation is made from the interaction of deductive and induction
Use of Data	Data acquisition aims to test assumptions or hypotheses relevant to an established theory.	Data collection aims to draw themes and patterns and then create the theory.	Data collection investigates a phenomenon, defines trends and patterns, and identifies them in a conceptual context. Then the collected data is used to explore these concepts further through data analysis and experimentation.
Theory	Endorsing or validating a theory.	Building a new theory.	Building new theories or modifying the current theory

In order to draw the whole image of research studies and their approaches, we need to include the classification of any research project. Such classification includes exploratory, descriptive, or explanatory (Hew et al. 2019). This classification (exploratory, descriptive, or explanatory) varies from one study to another as well as the research settings. Exploratory research aims to explore the topic further or to help researchers better understand the issue (Alayoubi, Al Shobaki & Abu-Naser, 2020). Literature review, observation, survey, and focus group will all be used to do exploratory testing (Farajallah et al., 2018). Flexibility, such that the direction of the study can be changed by new data acquired during the research, is one of the advantages of exploratory research (Alayoubi, Al Shobaki & Abu-Naser 2020). Thus the current study utilises the exploratory approach to explore the influence of social subsystems such as human and organisational culture. Where the technical subsystems include big data system quality and big data tasks. These social and technical factors could support the implementation of BDA in Saud Arabian Higher Education.

Descriptive research identifies a certain phenomenon under investigation (Saunders et al., 2009). Surveys, field testing, and content analysis are used to gather data for descriptive research. The explanatory analysis focuses on identifying and measuring relationships among variables. To better understand interactions between factors, as well as to clarify how and why anything happens, an issue is researched. Qualitative and quantitative data explain variables (Kim, Sefcik & Bradway 2017).

4.5. Research Designs

The term study designs refer to processes and activities for conducting a study that can help develop general conclusions to specific methods of data collection and examination (Creswell 2013). The research design process entails deciding on a method that would be used to analyse the problem. This choice depends on the researcher's viewpoint on the study's outcome, the process of enquiry, and the specific collection of data, examination, and interpretation. The design chosen often depends on the nature of the research problem, the study's primary audience, and the investigator's experience. (Creswell, 2009). The author also highlighted that there are three research designs which are qualitative, quantitative, and mixed form. The following paragraphs discuss those methods.

4.5.1. Quantitative Research

Various researchers have highlighted that the quantitative method always uses numbers to conclude the investigated phenomena (Berkovich 2018; Creswell 2013; Hargiss and Member 2017). Furthermore, Molina (2019) stated that a quantitative method is inextricably tied to natural science and uses surveys, experiments, and simulations to test the hypothesis and validate/propose a theory. In addition, quantitative analysis is concerned with formulating an assumption based on established ideas and amassing data quantitatively (Cress well. 2003). The data gathered would be analysed to determine the correlations between the hypotheses' (Bryman 2004). Thus, the quantitative analysis focuses on identifying and validating 'causal associations between concepts' (Bryman 2004,p. 31). Quantitative analysis, according to Johnson & Christensen (2008), is based on objective ontology and presupposes that human behaviours can be predicted for one or more reasons. The study and procedure are the primary quantitative study tools (Creswell, 2009). Cress also highlighted that questionnaires or are utilised in survey design to gather data from a representative population sample (Creswell, 2009). Equally important, the study of Bennerson (2021) states that a quantitative analysis design is the most effective method for determining the existence of interactions between two or more measurable variables, New statistical approaches broadened the study's potential for use in a wider population.

4.5.2. Qualitative Research

Qualitative research involves qualitative phenomena, such as examining certain forms of personal observations, events, and deep knowledge of social processes(Anikin 2021; Aspers and Corte 2019; Fàbregues et al. 2021; Jo Bennerson 2021). The authors stated that qualitative study uses several approaches, including in-depth interviews and in-depth examination of archival documents, and is focused on providing a full description of a particular event or unit. While qualitative research, like quantitative research, investigates a wide range of topics, it tends to concentrate on the meanings and motives behind cultural symbols, personal observations, events, and deep knowledge of social processes. In summary, qualitative research is concerned with comprehending processes, experiences, and the meanings that individuals ascribe to objects Fàbregues et al. (2021) define the qualitative method as a technique for examining the meaning in which people or groups associate with social situation. The research process includes developing study questions and methods for collecting the data in the participant's environment, analysing the data inductively by progressing from particulars to broad themes and interpreting the data's significance. The qualitative researcher gathers data from individuals in natural settings to study how people behave and act in the investigated social circumstances.

4.5.3. Mix Method Research

A research design describes the general approach and particular plans for discussing the research field of study (Creswell 2013). The research used a mixed-methods approach to accomplish this project. The combination of different techniques means using various analysis methods to gather evidence and analyse and discover, drawing conclusions based on both As a mixed methods analysis proposed, this concept yields a method that merges qualitative and quantitative approaches into a better-fit framework (Shaw et al. 2018). In addition, mixed methods analysis has developed with a perspective on pragmatism, and it has proven essential to combine research techniques to address relevant research questions embedded in real-world contexts. The two methods, qualitative and quantitative, have different practices, advantages, and drawbacks. Integrating quantitative and qualitative analysis is very common to enhance the evidence from the other side of the method (Huebner et al. 2017). In Addition, the study of blase (1993) highlighted the significance of quantitative data being utilised to provide broad trends, such as the levels of leadership efficacy, whereas qualitative data were employed to provide insights into how followers perceive leaders' attitudes. More importantly, Creswell and Plano Clark (2018) highlighted that utilising mixed methods is crucial since the qualitative method supports the quantitative approach's findings. The authors also stated that applying mixed methods allow the researcher to gain more insights and detailed data on the investigated phenomena. Therefore, a workable approach can be applied in the real world (Lan 2018). The objective was to explore the influence of social, and technological aspects that support the implementation of BDA in Saudi universities; a research design that was effective for implementation purposes was selected. Thus the sequential approach was selected to investigate the phenomena.

As justifications for using sequential exploratory mentioned above, related methodological reasons are crucial to discuss. For example, in their study, Greene et al.

(1989) asserted that triangulation, complementarity, development, initiation, and expansion are the primary reasons for applying mixed methods in any research project. Table 4.2 illustrates the types of mixed methods approaches applied in previous studies.

Table 4.2. Mixed methods design.

Type of Design	Priority of the Implementation	Analysis	Integration Phase	Theoretical Perspective
Sequential Explanatory	Quan then Qual	Equal Quan/ Qual	interpreting phase	Might be present
Sequential Exploratory	Qual then Quan	Equal Quan/ Qual	interpreting phase	Might be present
Sequential Transformative	Quan then Qual, or Qual then Quan.	Quan/ Qual or both	interpreting stage	Definitely present
Concurrent Triangulation	Quantitative and qualitative data are collected simultaneously using a triangulation technique.	equal Quan or Qual	interpreting phase or analysis phase	Might be present
Concurrent Nested	Quantitative and qualitative data collecting via triangulation in real-time	Quan or Qual	Anlaysis phase	Might be present

Concurrent transformational	Concurrent Data triangulation consists of collecting both Quan and Qual data.	Quan or Qual	Usually analysis phase; can be in the stage of interpretation	Definitely present

Qual: Qualitative method **Quan**: Quantitative method Source Plano & Cress well (2018)

4.6. The Research Design of this Study

It is critical to select the right study design approach because it dictates how the research data will be gathered and analysed (Creswell 2012). Each such method possesses its advantages and disadvantages. However, the investigator chooses the best approach for this study based on the research phenomena. This study gathered data sequentially - quantitative data were collected first, followed by qualitative data. As a result, quantitative data "Phase One" informs the protocol for the qualitative method "Phase Two". The usual mixed methods design was expanded by delving deeper into the qualitative data to understand the data gathered from the interviews. As Creswell & Plano (2018) suggested, it is better to collect quantitative data with large participant numbers than to gather qualitative data (interviews) with smaller numbers. While collecting and analysing quantitative data, I identified which quantitative findings required further investigation to obtain a more detailed explanation of the quantitative results (Anikin 2021).

This study used the quantitative method to examine the proposed research model. Nevertheless, deeper investigations are needed to address the topic since no research has been undertaken in Saudi Arabian higher education that examines the influence of socio & technical factors that promote BDA to improve decision-making by top management. Thus the exploratory character of qualitative research is paired with quantitative research design to help the researcher better grasp the problem, resulting in more generalisable conclusions. Besides the quantitative method's findings, it is also important to follow up on the quantitative results using a qualitative approach.

Surveys are used for quantitative data collecting since they are the most effective in achieving study objectives and answering research questions. Simi- structure open-ended question approaches are used for qualitative data gathering to verify the findings of the quantitative method. Figure 4.2 illustrates the methods applied in this study.

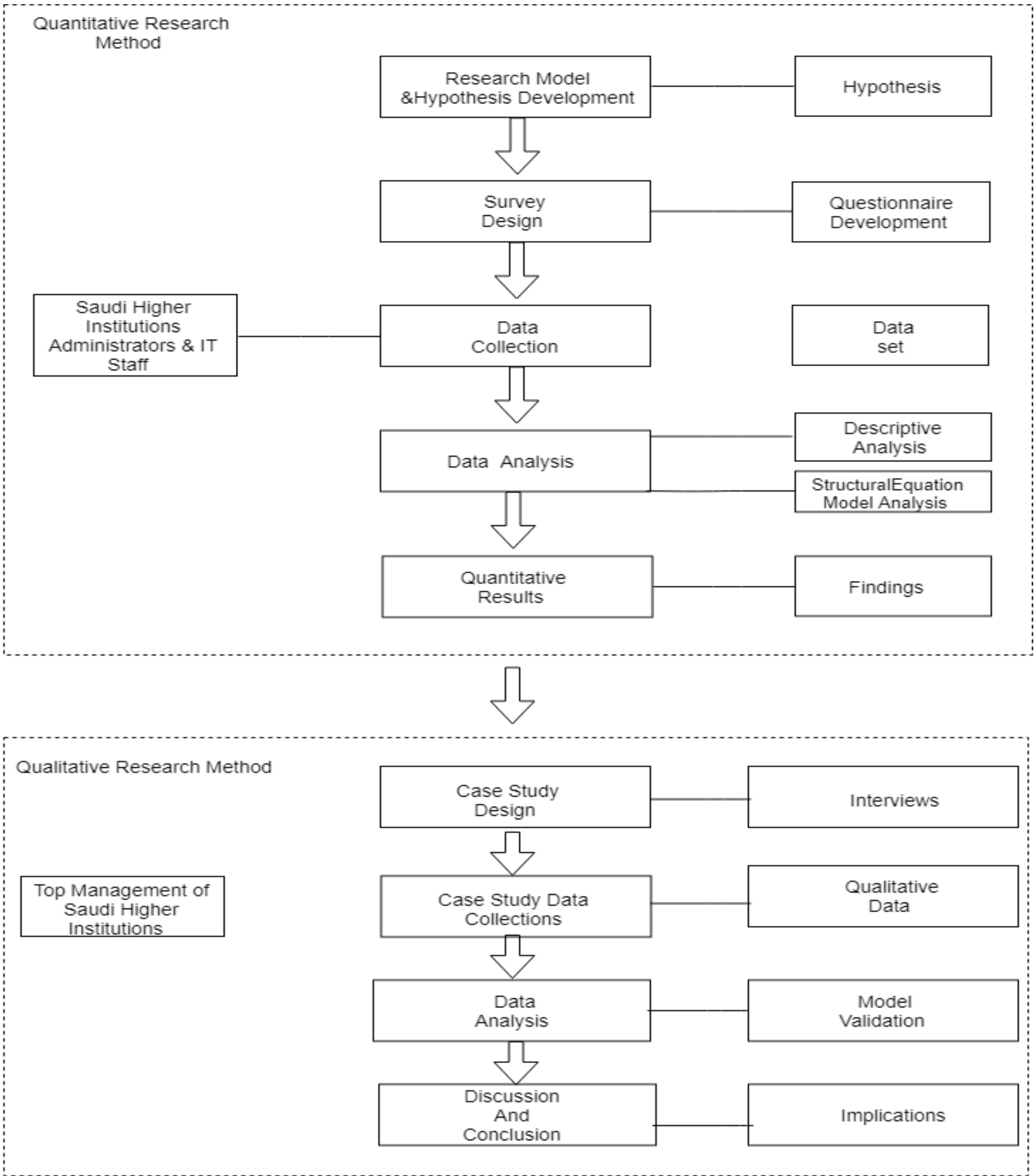

Figure 4.2.**Mix methods approach**

4.6.1. Justifications for Selecting Mixed Methods Approaches

Mixed methods are a sort of research that uses two or more methodologies to gather information. This approach can be used to compare the outcomes from two different types of study, as well as to examine how each approach influences the other. Mixed methods have been utilised in all areas of study, including social sciences and natural sciences, and there are many benefits to employing mixed methods (Creswell, 2003). Big data analytics BDA evaluates data sets from various sources, including text, software, and methodologies. The data collecting and analysis of data received from large data sources use diverse research methods. The BDA objective is to forecast the response behaviour or understand how the input factors link to a response (Casalegno, 2021). The employment of mixed approaches in this regard fulfils the criteria for assessing these various sources. Hence, this study chooses to use mixed methods for the reasons below.

Researchers can examine different perspectives and unearth hidden linkages between the numerous layers of our multifaceted study issues when they use a combination of quantitative and qualitative research methodologies (Makrakis & Kostoulas-Makrakis, 2016). This makes it possible to have a deeper comprehension of the linkages or inconsistencies between qualitative and quantitative data. It can compensate for the deficiencies of each approach. It has the potential to generate more convincing evidence and to instil greater trust in results. Besides, it can provide researchers with more granular findings than the results of each separate approach.

The combination of the two approaches enables the study of a significantly larger population than would not be possible with just one approach alone. For instance, the available options for responses in a questionnaire can limit the applicability of quantitative methodologies. Although qualitative approaches enable a wide number of participants to narrate their stories descriptively, the number of participants is a limitation of these methods (Lindsay-Smith et al., 2018). Triangulation is one of the most frequently used mixed methods, and its goal is to collect information that is different from other studies but related to the topic under investigations." It combines the merits and drawbacks of qualitative and quantitative research approaches, such as large sample sizes, trends, and generalisations (Heale & Forbes, 2013).

Using mixed methods, researchers can find reliable ways to study complicated topics, such as big data analytics (Brannen, 2005). These methods allow researchers to collect data from various sources, such as surveys, interviews, and direct observation of the issue. Big data analytics is one example of a complicated topic that can be studied using mixed methods. A/B testing is one of the methods that are utilised in BDA. This methodology entails contrasting a control group with several different test groups. The Mixed Method approach incorporates both standard A/B testing as well as traditional user experience research techniques adapted for experimentation (Nasiar et al., 2022). Similarly, the analysis of additional BDA approaches lends itself particularly well to the use of mixed methods.

4.7. Study Settings

Ensuring the sample represents the whole population of Saudi Arabian universities is vital. Thus, we have selected six Saudi Arabian universities placed in different locations within Saudi Arabia. Using this criterion for selecting those universities allows the researcher to ensure that the sample represents the whole population of Saudi Arabian academic & non-academic and top management staff working in Saudi universities. NU1, located in the northern part of Saudi Arabia, is the first selected university in this study. The second is SU1, which is located in the country's southern part. WU1 is the third selected university in this research, located in western Saudi Arabia. The fourth university is EU1, located in the eastern part of the country. The fifth university in this study is MU1, located in the middle of Saudi Arabia. The last selected university is WN1, located in North West of Riyadh (The capital of Saudi). Those universities were selected based on the university's location and diverse cultures. This diversity allows the researcher to ensure that the sampling size represents the whole population of academic and non-academic staff working in Saudi universities and allows the investigator deeply understand the phenomena. The next section discusses the Populations, sampling techniques, size.

4.8. Population & Sample

The population is defined by Kothari (2004) as the whole number of people or groups of individuals with common characteristics. In this study, the targeted population are IT academic and non-academic staff and decision-makers in selected Saudi Arabian universities. Since the population is very large, if we consider the whole of Saudi Arabian universities, surveying such population is impractical since it requires budget and time. Thus, the sample representing the whole population is needed for data collection.

Sampling can be defined as the targeted individuals selected based on certain characteristics in a way that it is a statistically valid representation of the entire population. (Etikan & Bala 2017). Therefore, the sampling process and these techniques will be discussed next subsections.

4.9. Sampling Techniques

A sample selection may be accomplished in two ways: through probability & non-probability sampling. Specifically, these strategies "offer various ways to limit the quantity of data you need together by exploring only data from small groups rather than all potential cases (Kim, Sefcik & Bradway 2017). Probability sampling, also known as a random or systematic sample, is a sample in which every member population is given the same chance of being picked from the population as a whole (Etikan & Bala 2017). The sampling approach determines the sample size required for research and then picks a sample that is big enough to give accurate estimates by assuming that every element of the populations has non-zero possibility of being selected from the population. It has a higher degree of generalisability when transferring the results from it to a bigger population. Types of sampling are included but not limited to probability sampling, basic random sample, stratified random the, systematic random sample, and the cluster sample. (Etikan & Bala 2017, p.1). Each sort of probability sample has its own set of benefits and drawbacks to consider. Simple random sampling refers to every population member having the same chance of being selected. (Rahi 2017). This is frequently utilised in cases where there are many units or precincts rather than in instances where little information is available about each unit. It is a basic kind of probabilistic sampling that includes selecting every member from the population, and it is used in many studies. If the population has a specified interval or ratio scale, and the number of elements picked from each stratum is proportionate to the size of that stratum, this sampling approach can produce unbiased population parameters. In stratified random sampling, the population is separated into subgroups known as strata before being randomly sampled (Rahi 2017,p.3). The strata should be mutually exclusive and collectively exhaustive to function properly. Before sampling, the first cluster sampling technique entails partitioning the population into groups that are sampled from each group. These clusters may be as vast as entire cities or as tiny as a single storefront location; the number of individuals inside each cluster is determined through the number of established individuals within each cluster.

In situations where the researcher is unsure of how to identify the sampling frame or where the sampling frame is unknown or unavailable, non-probability sampling is utilised (Rahi 2017,p.3). Instead of being quantitative, such a sample's purpose is frequently qualitative in quota sampling; the population is separated into groups before being sampled. For example, if a survey of American people is conducted, the results might be broken down by age group, gender, economic level, and other criteria. A method known as "probability proportional to size" (PPS) is used to choose members of a population after it has been separated into groups. Once the population has been divided into groups, individuals from each group are selected for inclusion in the sample. This approach is most successful when examining "hard-to-find" populations, which means elusive groups or people or tiny groups or individuals who are difficult to discover. The purposive sampling method is most effective when investigating "hard-to-find" populations (Etikan 2016).

In an interview or survey, a snowball sampling strategy is used in which information or views are sought from the initial respondents, either directly from them or indirectly via asking another responder about the same product or brands, for example. This additional responder may participate in a survey, providing the interviewer access to their names and other important contact information (Etikan 2016). This is referred to as self-selection sampling when a nonprobability sample frame is used to collect data from a population. This approach is most commonly employed in convenience sampling. In this instance, the subjects determine whether or not they choose to participate in the study by being questioned.

Finally, convenience sampling is one of the most often used sampling approaches because it allows researchers to pick people who are simple to reach and interview. Choosing individuals that willing and able to engage in the research study is vital for this stage. Therefore, the results of the findings of this study can be generalised to the whole populations (Kothari 2004). The study's intended audience includes both IT academic and non-academic staff. The goal is to generalise the findings of the investigation to everyone.

In other words, the sample error must be as tiny as feasible and non-significant (Kothari 2004). Generally, the bigger the sample size, the lesser the chance of encountering sampling errors. Therefore, Kothari (2004) stated that "when selecting a sample technique, the researcher should ensure that the approach results in a small sampling error and assists in the management of systematic bias."

This method ensures that all population elements are equally likely to be picked because it is based on random selection. This strategy was selected because it reduces population bias while maintaining data accuracy. Consequently, this study used the snowball sampling approach to perform quantitative research to answer the research questions. A simple random sample does not assure that each branch of the population is represented in the numbers collected for each branch of the population.

In order to conduct this qualitative study, we utilised two sample techniques: self-selection and purposive sampling. During the first step of self-selection, we obtained the participants' free agreement to participate in our study, after which the questionnaire survey portion of the study was completed. Finally, the contact information was made available. This was done in order to reach out to people in order to organise the interviews. The approach we utilised in the first step is commonly used in research to decrease the amount of time spent picking acceptable instances and to speed up the process. Additionally, this strategy makes the high involvement rate possible (Etikan & Bala 2017).

4.10. Participants' Sample' Size

The number of people that took part in a study is referred to as the sample size. It refers to the features of the population that is the subject of the investigation (Kothari 2004,p.56). The sample sizes will likely be big if research is conducted using probability sampling. It is also true that the largest the sample size, the greater the researcher's trust in the findings. Besides, when using a large sample size, there is less chance of making a mistake in generalising the findings. Therefore, a critical part of sample design is determining the sample size that will produce the best results.

Furthermore, this sample size must be ideal from both a statistical and a cost-effective standpoint. Therefore, based on the recommendations of Kothari (2004), the following standard was used to determine the ideal sample size: sampling, study population size, availability of funds, technical investigator and available time, and the nature of the investigation. Consequently, 270 participants took part in this survey, which was conducted considering the abovementioned parameters.

4.11. Methods of Data Collection

Several data collection methods include surveys, interviews, and focus groups. The approach is "most appropriate for your study is determined by the objectives of your investigation" (Kothari 2004,p.100). According to Punch (2009, p. 290), "qualitative approaches could be effective in areas where quantitative methods are ineffective, and quantitative methods can be effective in areas where qualitative methods are ineffective." In addition, quantitative methods can be strong in regions where qualitative methods are poor. Integrating these two approaches creates a chance to combine these two sets of strengths while accounting for their respective deficiencies.

Consequently, Data-gathering methods were employed, including semi-structured interviews and a questionnaire survey to gather the data. The following subsections provide in-depth explanations of the strategies that were chosen.

4.11.1 Quantitative Data Collection

We used a questionnaire to gather information for the quantitative data collection approach. As described by (Kothari 2004,p.100), a questionnaire is " a set of written questions that have already been evaluated, with answers being recorded by the respondents from a predefined list of options." If the researcher understands exactly what he or she wants, how to measure the aspects of interest, and how to interpret the data that results, they are frequently utilised. The individual who does the research is aware of how the data will be obtained and what the researcher intends to investigate. Questionnaires can be sent in various ways, including via mail or online (Ebert et al., 2018). The questionnaire design, the questionnaire translation procedure, the questionnaire's pretesting, and the questionnaire's pilot study are all addressed in further detail below.

4.11.2. Questionnaire Design

In scientific investigations, questionnaires are used to collect data from participants. How questions are posed can impact the number of persons who answer them and the veracity with which they do so. Before you use a questionnaire, you must carefully design the questions, ensure that the questionnaire's layout is attractive, and ensure that people understand why you are asking them the questions before they fill out the questionnaire, test the questionnaire on a small number of people first, and have a solid plan in place for before and after you distribute the questionnaire. There are three things that a researcher should be on the lookout for. The first thing a researcher should consider is how to construct his questions in such a way that people would be able to answer them. He should utilise basic language because some readers will have difficulty reading large text passages. He should also try to gather information from his interviewers so that he may inquire about it in his next interview. This research thoroughly considers each question's objective and its use of straightforward language. As a result, all participants can comprehend the phrases used in the agreement. It was decided to use closed-ended questions since they require less time to answer and allow for more thorough analysis of the responses. People have informed us that they would have stated something different if we had asked them more questions, so we have added extra open-ended questions after the survey to reflect this. The questions that were confusing and lengthy were eliminated from consideration.

We named the variables "larger" and "smaller," respectively, to indicate their relative sizes. The Likert scale is being used. Then we rated each number on a scale of one to five stars. For example, 1 indicates "strong agreement," whereas five indicates "strongly disagree." A5 is a five-point scale. This scale was chosen because it is easier for participants to read the items and complete the questionnaire, and it is also one of the most regularly used scales of measurement in the world. The Likert scale with five points was chosen because it is easier for participants to understand the items and complete the questionnaire, and it is one of the most regularly used scales of measurement in the world. In addition, the survey was straightforward, well-organised, and simple to read, with clear instructions on responding to each question.

The translation of the questionnaire was the first stage in verifying it. Except for the first, all questions were translated into Arabic (see Appendix B). In order to ensure accurate translations, two back-translators reviewed and approved the translated versions of the questionnaire. Because Arabic is the official language of Saudi Arabia, this was done.

The major body of the questionnaire was separated into three sections, each containing different information. The technology of big data analytics (BDA) was initially introduced in a nutshell. The BDA technology was discussed first because it is a new idea in Saudi Arabia and is still in its early stages. However, many businesses and academic institutions are attempting to deploy their systems using BDA technology. The first portion contains the questions' answers and the respondents' information. It included information on the university, gender, age, years of experience, and roles at the university. In addition, their analytical tools are used at the university. To begin, the respondent was provided examples of how to reply to Likert scale questions about the research factors using a Likert scale. The components of the proposed model are used as the basis for the questions in this subsection.

The factors are as follows: First, the researcher starts with the influence of social subsystem aspects, i.e., the impact of BDP on BDS. Second the impact of social factors, i.e., organisational factors, on BDS and BDT, respectively. The third social factor is the impact of organisational culture on BDS Fourth is the influence of organisational culture on BDP. Fifth, how does the organisational culture influence BDT.

Regarding the Technical subsystem aspect of BDA, such as Big Data System BDS and Big Data Tasks BDT, on improving the decision-making. Lastly is the impact of improvement of the decision-making process by top management on enhancing university performance. Items that have been verified in previous research are utilised for the measurement. In addition, questions are rated on a five-point scale, in which selecting 1 meaning that strongly agree with the statement and 5 strongly disagree.

4.11.3. Questionnaire Translation

The questionnaire was translated from its original language of English to Arabic. It was ensured that the questionnaire in the original language corresponded exactly to the questionnaire in the translated language before distribution. Later, the translated version was offered to the language specialists, who gave their opinions. They double-checked the translations to ensure that the instrument was understood clearly. The researchers also conducted a comparison between the English survey and the translated version. To summarise, the translation of the English version into the Arabic version has been finished. Second, two professors were consulted for their opinions. They went through the translation one more time. They were students at Macquarie University Australia, where they studied English. The Arabic translation has been revised in response to their suggestions. Third, there was another evaluation of the translation process. This time, it was written and proofed by Wattad translation services in Sydney by a teacher specialising in the Ar, who works as a teaching assistant in one of the Saudi Arabian universities. Grammar, language, clarity concerns, and the ease with which the questionnaire could be completed were all examined. The criticism was taken into consideration and incorporated into the content. Grammar, language, clarity flaws, and the questionnaire's overall simplicity were all addressed. The three processes mentioned above confirmed the quality of the Arabic version of the questionnaire, which was also evaluated during the translation process.

4.11.4. Pretesting and Pilot Study

Pretesting usually raises the likelihood of a successful pilot study (Zaza et al. 2002). When pretesting is carried out, the likelihood that pilot testing will be relevant to the practical environment increases, and the transferability of results increases as a result. On the contrary, "pretesting" helps to verify that questions are "properly phrased, understandable by all respondents, and relevant to the issues at hand" (Kothari, 2004).

However, validity refers to how precisely a set of data collection processes represents the phenomenon being investigated. " (Taherdoost 2016). Face validity is seen as "a fundamental and bare-bones indicator of the legitimacy of content" (Taherdoost 2016,p.29)

The questionnaire design was subjected to a preliminary test. Ph.D. students, as well as academic staff working in Saudi universities, who will be a part of the study. The goal was to look for any language or technical issues that could have occurred.

A selection of participants was made based on their ability to identify concerns with the arrangement, clarity, and ambiguity of the questions and the questionnaire in general. Experts were eventually called in to undertake the examination. First, they examined the questionnaire's validity (both in terms of its appearance and content (Creswell & Plano Clark 2018). The following factors were taken into consideration during the pertest: Four experts in the research field, two academic staff from the student learning centre at the

University of Sydney who have experience in questionnaire design, and two academic staff working at Jeddah University who have experience in statistics and questionnaire design. The suggestions we got were for language, rearranging a few questions, and the overall arrangement of the questions. Changes were made to the questions as a result of these findings. The author also performed two pilot investigations. As a result, the questionnaire's reliability and validity were increased due to the study.

4.11.5. Quantitative Data Analysis

Smart PLS3 programme was used to analyse the data demographic (Descriptive statistics). When the goal of a study is to predict or discover constructs, the PLS-SEM approach is seen to be appropriate. There are two types of Structural Equation Modeling; covariance-based and partial least-squares are two forms of structural equation models. One uses a composite model estimation technique, while the other uses a common factor model estimation (Ringle et al., 2020). The common factor approach relies on the hypothesis that "the variance of a group of indicators that might be adequately described by the availability from one unobserved variable. While the composite approach presumes that compositions are defined by combinations of indicators" (Ringle et al., 2020).

As a result, Smart pls3 was selected since our investigation's goal necessitates using CB-SEM. Furthermore, Smart-PLS is an effective software with many advantages. This tool is simple enough that even a complete novice may produce parametric forms in a short period. In SEM, we employed two stages: first, we measured the reliability & validity of the proposed model, and then we tested hypotheses based on the results obtained from those tests.

4.12. Qualitative Data Collection

Qualitative methodologies were employed to achieve the aims of this study. Qualitative data-gathering approaches such as online and face to face interviews were employed in this study (Kothari 2004). The next sections discuss description of the employed qualitative data-gathering methodologies.

4.12.1 Semi Structure Interviews

It was decided to do the online interviews. Decision makers, senior managers, and data scientists were among those who took part in the interview. The interviewees were all employed in Saudi Arabian higher education institutions. The investigation aims to gain in-depth details on how social and technical subsystems lead to improving executives' decisions in Saudi HEIs. It provided light on the significance of social and technological factors in big data analytics and its impact on decisions making and university performance. The responses of the interviewees were analysed. It demonstrated that interviewees were treated to the appropriate set of questions. It was in accordance with the aims of the study methodology.

4.12.2. Sample Size

It was decided to perform a mixed-technique study. Accordingly, 17 interviews were performed with the participants. The interviews include IT academic & non-academic staff and top management staff in Saudi Arabian universities. Interviews give the researcher a deeper understanding of the phenomena being investigated. In the light of the sample size, the saturation might identify the sample size in the qualitative study. Data saturation is the process in which no new information and codes can be discovered by conducting new interviews. According to Guest et al. (2006), data saturation is not always predicted by the amount of samples; rather, it is identified during the data-gathering process and is shown when no new codes appear after additional sampling (Dull Charles, 2018). For instance, fewer organisations would need to be sampled to reach data saturation if multiple organisations were preparing volunteers to collect identical data. This fact would not be known before the study. Likewise, the stage of category development known as theoretical saturation occurs when no new characteristics, dimensions, or connections appear through analysis. Saturating the data means there is no more or less information available than is necessary for the study (Saunders et al., 2018). In order to ensure that no new information was being uncovered, I conducted interviews with "validated" individuals until data saturation was reached. In order to establish when I had reached data saturation, I analysed the responses as they came in and modified my questions accordingly. Saturation of the data set was accomplished through interviews with all willing participants across the many enterprises engaged in big data research (Knapton, 2020).

The type of qualitative research design will determine the sample size, according to Creswell (2014). The author noted that the normal range of phenomenological research is between three and ten, based on his assessment of the literature. As a result, the research sample of 17 IT academic and non-academic staff, and top management staff in Saudi Arabian higher education was appropriate for the chosen exploratory study, as the research did not aim to develop a theory.

The sample for this study size is commensurate with a number of mixed-method studies on the same subject that have recently been undertaken and have included 8-12 interviews. The next sections will discuss the pilot study of the interviews, qualitative data analysis, and the validity of the questionnaires.

4.12.3. Pilot Study for Interviews

"Pilot tests are small-scale studies designed to test a questionnaire, interview checklist, or observation schedule in order to reduce the likelihood of respondents having difficulty answering the questions and of data recording problems", as well as to allow to evaluate the questions' validity and reliability (Kothari 2004,p.17).

Pilot studies for interviews help the researcher to identify any weaknesses in the survey method and to check that the data collected will be meaningful information for the study's objectives. A pilot study does not take many resources and may be completed in a short time, but it is significant because it allows researchers to determine how reliable their data will be before proceeding with the main study. The greater the number of interviews you do, the more in-depth your grasp of the market becomes. It is highly recommended that you do at least one pilot research to ensure that interviewers are asking relevant questions and that participants provide helpful feedback. Having a successful focus group will allow you to gain confidence and guarantee that the group is a success.

The questions were the same as those in the suggested research model, which was considered throughout the quantitative phase of the investigation. During the quantitative phase, they had previously been validated by a sample of respondents from the target demographic drawn from the target population—the "survey was posed in Arabic, of course. During the interview, questions were asked in Arabic. Three PhD students also advised that the interviews be restructured differently. As a result, the design was altered. Then, four academic staff working in Saudi universities were chosen to participate in a focus group pilot research. It was done through the use of convenience sampling. The pilot phase assists in determining whether or not the questions were clear and the amount of time necessary to perform the focus group sessions. The questions had to do with the recommended model factors prepared in the timetable, and they were all connected. The participants were asked about the readability of the questions; they also were asked if they found any difficulties in comprehending the questions and any other concerns they had with the questions in general.

4.12.4. Qualitative Data Analysis

According to Creswell & Plano Clark (2018), there is a great depth method for analysing qualitative data to understand the investigated phenomena better. Semi-structured interviews were selected as the qualitative method for the current research. They were later recorded and transcribed. In data analysis, four stages must be completed depending on qualitative characteristics (Creswell, 2009). The first step is to arrange the transcribed material and prepare it for further investigation and analysis. The second step is to examine the data. The ultimate objective is to have a general grasp of the facts in question. The data is then grouped using chunking and coding techniques. After that, categories are created. It provides context for data. The same procedures were used for our investigation. First, the information was typed into a computer. It had been programmed. After that, it was classified. The factors of the suggested model were taken into consideration. The additional categories were created to accommodate open-ended queries. There were new challenges to overcome. Those challenges related to the very detailed data and long answers from participants, which were unrelated to the research objectives. Thus, the researcher filters the responses of the participants and categorised them into the related themes.

4.12.5. Validity of the Questionnaire

Validity is concerned with whether the findings are truly about what they appear to be about," according to the dictionary. The term validity " validity refers to how precisely a set of data collection processes represents the phenomenon being investigated " (Kothari 2004,p.73). Validity can be divided into two categories: content validity and construct validity. Both sorts of materials were utilised. A measurement instrument's content validity is "the degree in which a given set of measurements provides sufficient coverage of the issue being addressed" (Kothari, 2004, p. 74). It is impossible to quantify in a numerical manner. Experts, on the other hand, can gain access to it. They have access to it in order to satisfy the requirements. The content validity was examined using both the pertest and the pilot research. Whereas the construct validity of your measurement questions refers to the degree to which the measurement questions truly assess the presence of the constructs, you intended to measure (Taherdoost 2016). In addition, Hair et al. (2017) evaluated the recommendations for convergent and discriminant validity.

The following criteria are used to determine how reliable the study is: credibility, transferability, dependability, and confirmability, among other things. In addition, the interviews evaluated its reliability and validity. Credibility is the key to determining the validity of the findings.

According to the interviewees, they were required to read the transcriptions of interviews that were relevant to them in order to maintain credibility. Therefore, this study's trustworthiness was established once the participants verified that the interviews were correctly recorded and transcribed.

Discussions with academic staff at higher education institutions in Saudi Arabia can be used to determine the appropriateness of the interviews. It assesses the consistency of the qualitative method, which may be developed and referred to be auditable when another researcher can follow the researcher's decision trail (Venkatesh, Brown & Sullivan 2016)

This means that if the data is handed to another scholar with almost the same perspective, the researcher follows a defined analysis technique, and he or she should come up with similar results. In most qualitative studies, the researcher is essential to the research instrument. Thus, the researcher's credibility was enhanced by performing pilot interviews with three academic staff in Saudi Arabia to establish and refine interviewing skills to resolve any issues that may occur during the interviews. Finally, confirmability means impartiality and accuracy to the data (Ryan-Nicholls & Will, 2009). The freedom means that the interviews are free from biases in the study process and outcomes" (Ryan-Nicholls & Will, 2009, p. 78). Confirmability is determined by assessing the correctness, relevance, and integrity of data of information (Ryan-Nicholls & Will, 2009). As a result, Confirmability was accomplished in interviews because the above three criteria were met (credibility, transferability, and dependability) (Ryan-Nicholls & Will, 2009).

4.13. Ethical Issues

The following actions were followed to ensure that the research was ethically managed. First, the consent of the concerned university was requested, and granted. The participants in this study were informed of the study's goals and objectives, which included the significance of social and technological variables in big data analytics. Fourth, they were informed that the findings of this study would be useful to decision-makers at higher education institutions and cloud computing service providers. Third, informed permission was obtained from the participant's right from the commencement of the investigation. Fourth, personal information was safeguarded and treated with courtesy. Fourth, all personal and sensitive information was kept and coded in a password-protected folder with a digital signature. It is only available to the researcher who is doing the research. Using letters and numbers instead of names safeguards the participants' privacy. Fourth, the information was handled with the strictest of confidence. The willingness of the respondents to participate was a determining factor in their involvement. They can withdraw at any point during the process.

4.14. Chapter Summary

This chapter discussed the research approach that was employed in order to complete the research. The design employed a hybrid method approach. For data collecting, a combination of quantitative and qualitative methodologies and rationale were used. There was a dispute over how the sample size was determined, the target demographic, and where the study would take place. A survey questionnaire, an open-ended question, and a focus group were all used to gather information for this study's findings. These strategies were thoroughly discussed throughout the meeting. First, the quantitative and qualitative phases' methodologies for conducting analyses were described. Next, the instrument's validity & reliability and the focus group were discussed. Finally, ethical issues were discussed at the end of the chapter.

CHAPTER 5

Descriptive Data Analysis

5.1. Introduction

This chapter is an in-depth data analysis describing the demographics and the study scales. Hence this chapter will cover the study participants' profiles concerning their bio, socio, and corporate graphics. This chapter will also cover measurement scales in terms of frequencies, means, standard deviations and percentages with the help of tables and graphs. Other descriptive details such as correlations, multicollinearity among scales and scale items will be covered in Chapter 6

5.2. Demographics Analysis

The demographic data collected in this study included participants ' gender, age, education, nationality, work university, work experience, job roles, BDA experience, information systems associated with BDA, and BDA tools. The detail on demographic variables is summarised in the following section.

Gender Profile: As shown in Table 5.1, 52.59% of participants were male, 36.67% were female, and 7% preferred not to say. 3.33% of the responses had no gender information, so these were marked as missing. It was predicted that there would be a variation between the percentages of "Male" and "Female" participants since 15.8% of the Saudi labour force is "Female" (World Bank, 2021). Gender profile can also be viewed in Figure 5. 1.

Table 5.1. Gender Profile

Gender	Frequency	Percentage
Male	142	52.59%
Female	99	36.67%
Prefer Not to Say	20	7.41%
Missing Values	9	3.33%
Total	**270**	**100%**

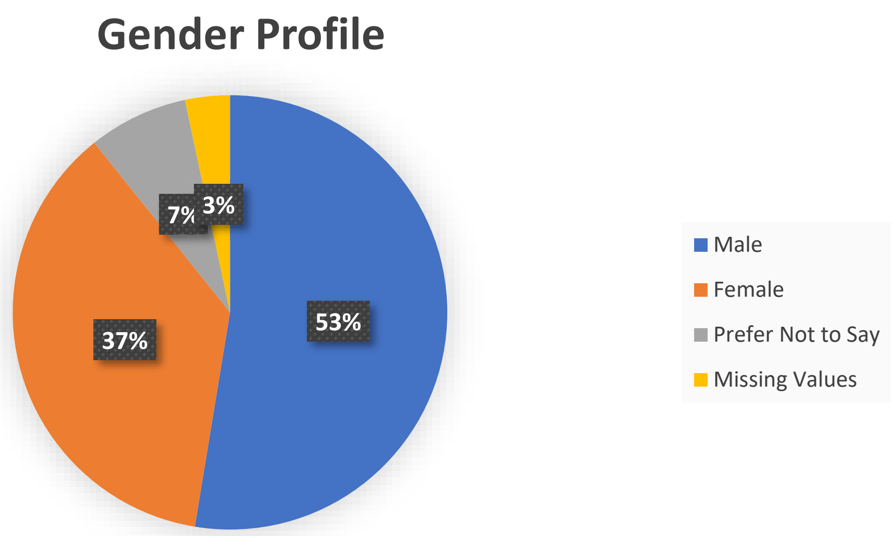

Figure 5. 1. Gender Profile

Age Groups: Regarding participants' age, the majority were aged 26-35 (55.19%), followed by those aged 36-45 (28.89%). Very few participants aged 18-25 (7%) and those above 45 years (7%). We also had 1.85% missing values. See Table & Figure 5.2 below.

Table 5.2. Age Groups

Age (Years)	Frequency	Percentage
18-25	20	7.41%
26-35	149	55.19%
36-45	78	28.89%
45 and above	18	6.67%
Missing Values	5	1.85%
Total	**270**	**100%**

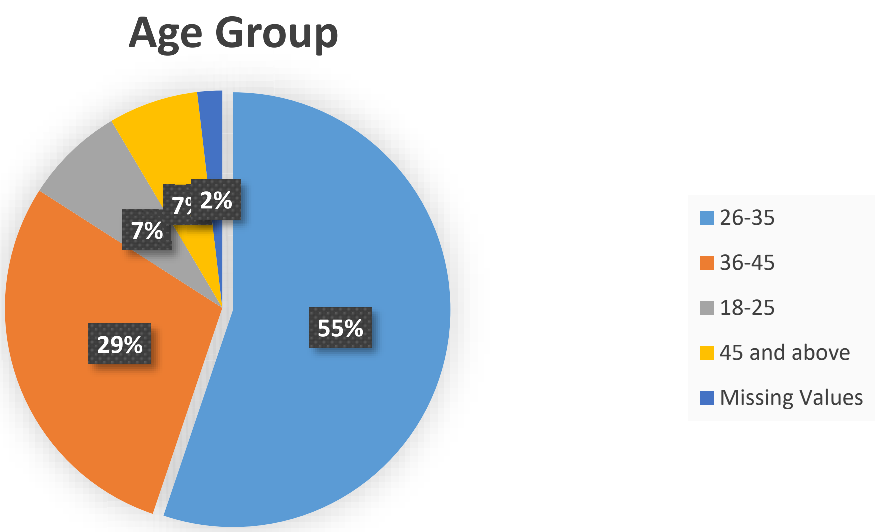

Figure 5. 2. Age Group

Educational Qualification: Table 5.3 show that majority of participants had a Master's Degree (42.96%), while PhD and Bachelor's Degree holders were the same in number (22%), 11.11% of respondents had a Diploma, whereas one participant stated to have some other qualification (0.37%). 1.85% of the values were missing. These details are given in Figure 5.3.

Table 5.3. Educational Qualification

Education	Frequency	Percentage
Master	116	42.96%
Doctorate	59	21.85%
Bachelor	59	21.85%
Diploma	30	11.11%
Other	1	0.37%
Missing Values	5	1.85%
Total	**270**	**100%**

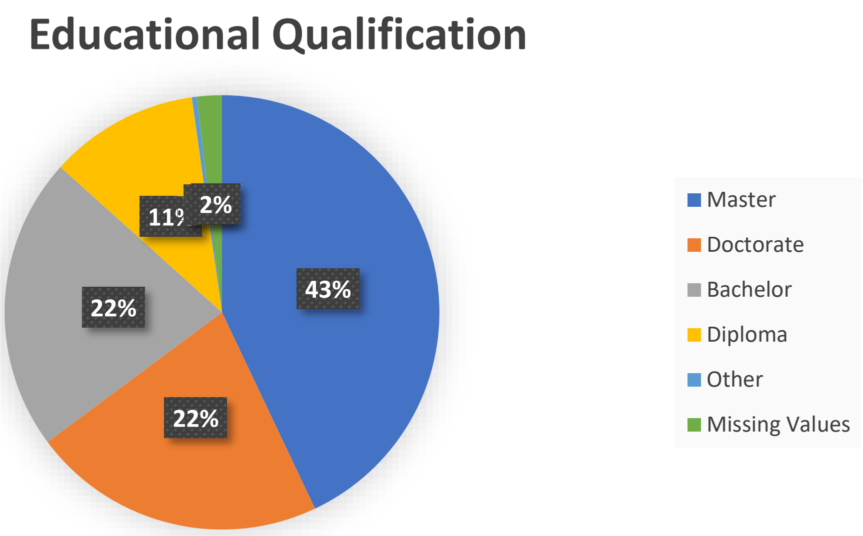

Figure 5.3. **Educational Qualification**

Nationality Statistics: Most of the respondents were Saudi nationals (81.11%), and 10.37% of the respondents were non-Saudis burn in Saudi. Where 7.04% of the respondents were non-Saudis but burned in Saudi, we also had 1.48% missing values. Details on the nationality of the participants are shown in Table & Figure 5.4.

Table 5.4. Nationality Statistics

Nationality	Frequency	Percentage
Saudi	219	81.11%
Non-Saudi	28	10.37%
Non-Saudi - Born in Saudi	19	7.04%
Missing Values	4	1.48%
Total	**270**	**100%**

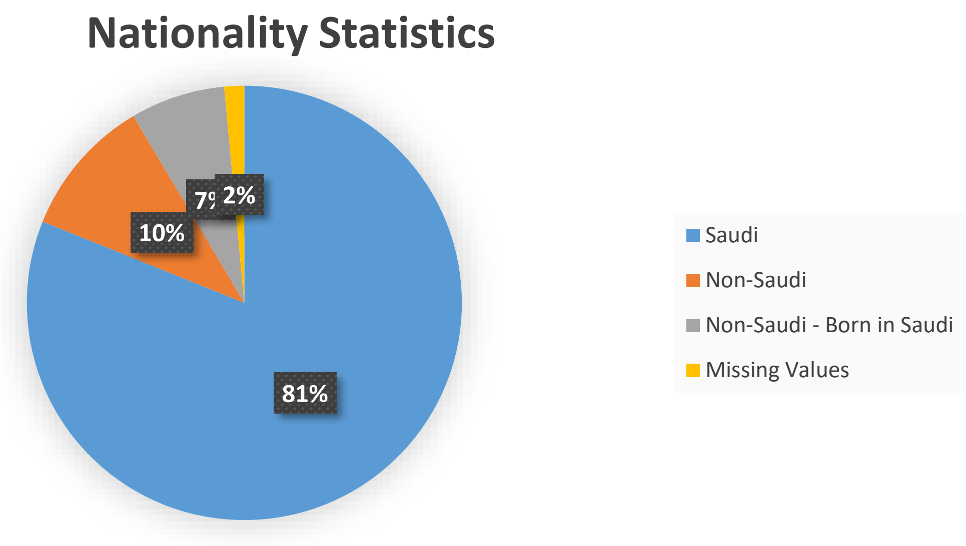

Figure 5.4. **Respondents Nationality**

Work University: Our study focused on big data and its influence on organisational performance in the Saudi Arabian Higher Education Sector. As presented in Table & Figure 5.5 that the mainstream of participants was working at SU1 University (30.81%), followed by NU1 (20.37%), WU1 (13.77%), and MU1 (13.33%). UNU1 is the second last university in terms of participant numbers in this study, with 10.77%) EU1 is the least number of participants among selected universities, with (8.52%). However, Participants from other Saudi universities also participate in this study (3%). Figure 5.5 also depicts the same details for visual assessment.

Table 5.5. Work University

University Name	Region	Frequency	Percentage
SU1	South	83	30.81%
NU1	North	55	20.37%
WU1	North	38	13.74%
MU1	Middle	35	13.33%
WNU1	Wester North	29	10.77 %
EU1	East	23	8.52%
Others	All	7	3%
Total	All	**270**	**100%**

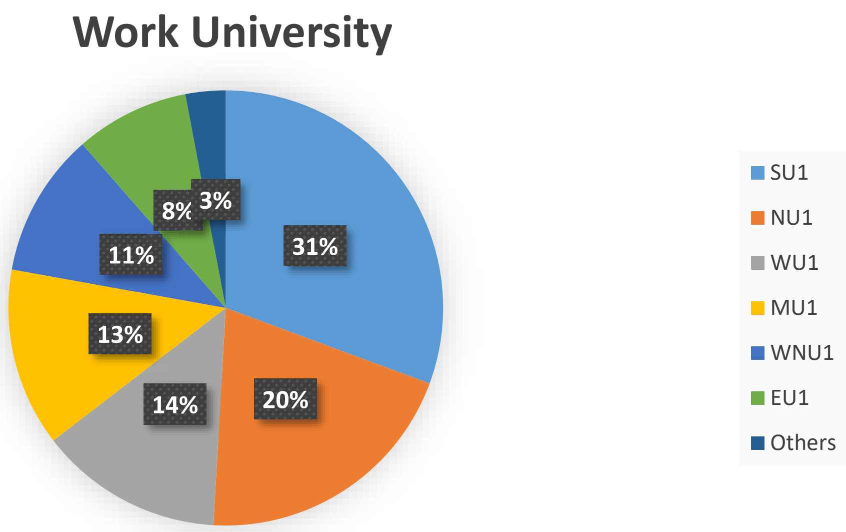

Figure 5.5. Work University

Work Experience: Total or general experience statistics are given in Table and Figure 5.6, where we notice that most respondents (50.74%) had >5 years of experience. Then 20% had 2-3 years of work experience, and 17.04% of the respondents had 4-5years' experience. Then we had respondents who had 1 year of work experience (7.04%), followed by 3.33% of participants have lesser than a year of experience. 1.85% of the values were declared to be missing. Experience profile can also be viewed in Figure 5.6.

Table 5.6. Work Experience

Experience (Years)	Frequency	Percentage
More than 5 years	137	50.74%
2-3 years	54	20%
4-5 years	46	17.04%
One year	19	7.04%
Less than one year	9	3.33%
Missing Values	5	1.85%
Total	**270**	**100%**

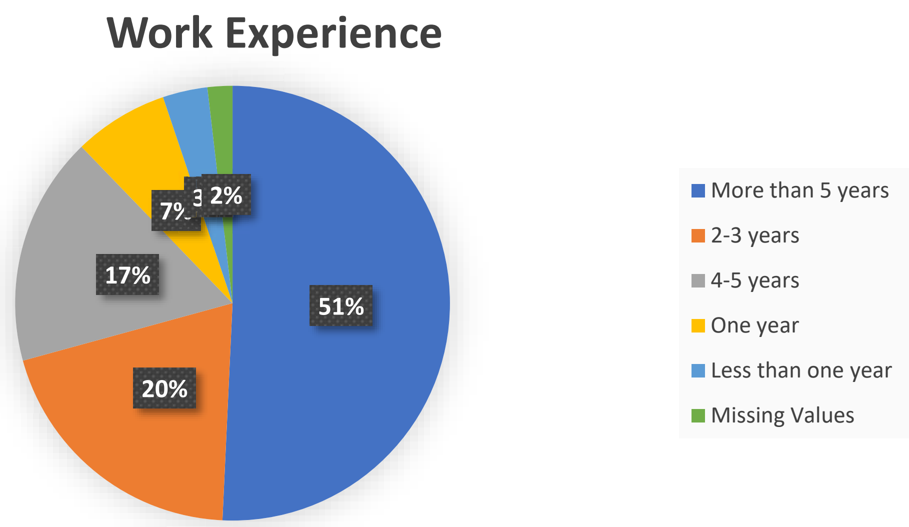

Figure 5.6. **Work Experience.**

Job Roles: The major roles undertaken by the participants were IT-related See Table and Figure 5.7, including Information Technology Academic Staff as the major responding population of the study (47.04%). 27.78% of the participants were performing their duties as Programmers / Developers. We had 11.11% of respondents working as IT Executives / Managers, while 5.93% were deputed in the University Deanship's IT discipline capacity. We also had 1.85% of Deans of IT Colleges, whereas 6.3% of values were missing. Lastly, IT technicians were not participate in this study with 0%. See Table and Figure 5.7 for a graphical representation.

Table 5.7. Job Roles

Job Role	Frequency	Percentage
Information Technology Academic Staff	127	47.04%
Programmers – Developer	75	27.78%
Information Technology Executive Level / Information Ttechnology Managers	30	11.11%
University's Deanship of Information Technology	16	5.93%
Dean Collage of IT	5	1.85%
Missing Values	17	6.30%
IT Technician	0	0
Total	**270**	**100%**

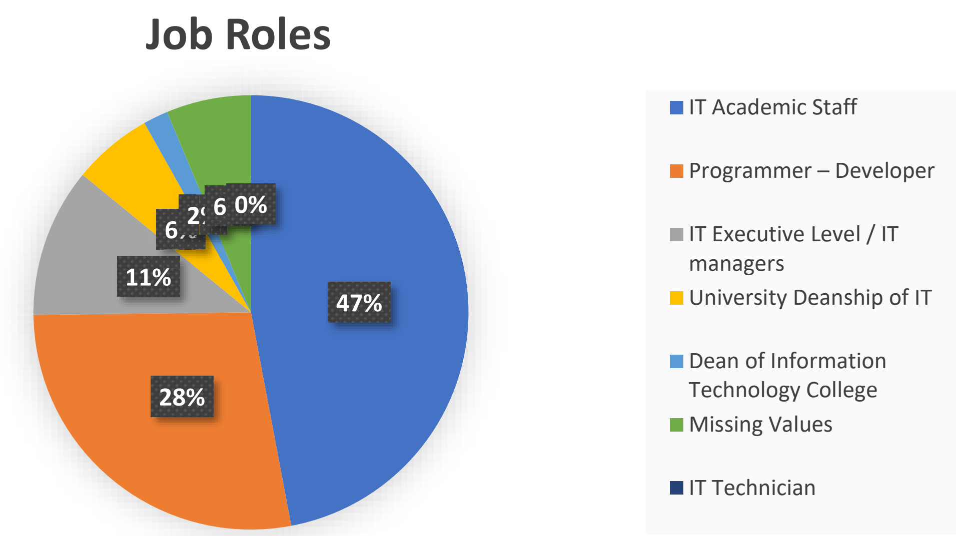

Figure 5.7. Job Roles

BDA Experience: Almost all respondents had IT-related careers, so we assessed how many of them had the experience in big data analytics. As shown in Table and Figure 5.8 that 203 (75%) participants had BDA experience, while 67 (25%) had not. See Figure 5.8.

Table 5.8. BDA Experience

Big Data Experience	Frequency	Percentage
Yes – Had Experience	203	75%
No – Had No Experience	67	47.03%
Total	**270**	**100%**

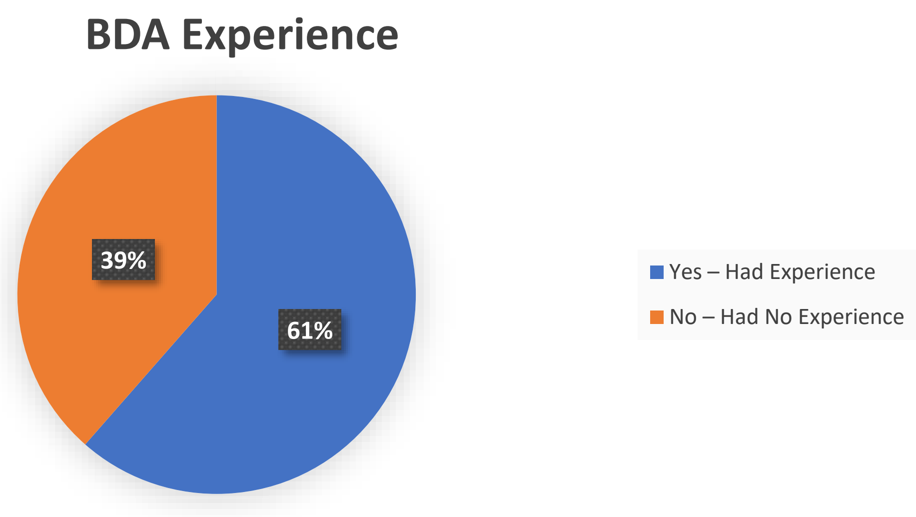

Figure 5.8. **BDA Experience**

Information System Associated with Big Data: We asked respondents about their usage of big data analytics in their organisations, particularly the information systems associated with big data, tools adopted, and decisions enabled by big data. Participants who prefer not to specify that system used with big data are the highest among the participants, with 60%. The Management of the information system decision support system is the second higher scale which participants with Management of information system chose. A decision support system has been chosen by the participants, with 11%. The exclusive information system is the second last with 8%. Lastly, Transaction processing systems are selected among the participants with 6%. The data distribution about BD systems usage is summarised in the table and figure 5.9

Table 5.9. Information System Associated with Big Data

Information System& Big Data	Frequency	Percentage
Not Specified	162	60%
Management Information Systems	41	15%
Decision Support System	29	11%
Exclusive Information System	22	8%
Transaction processing systems	16	6%
Total	**270**	**100%**

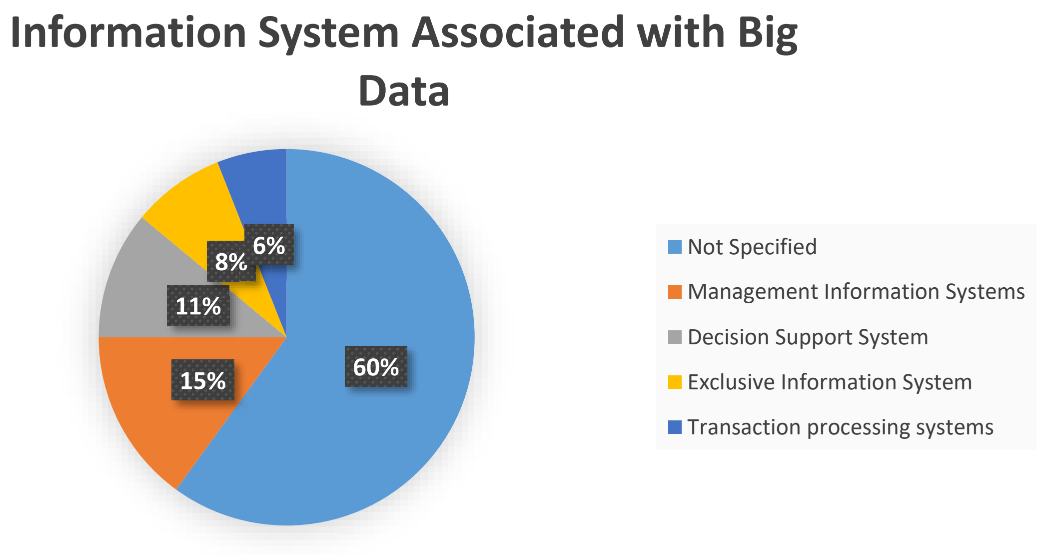

Figure 5.9. **Information Systems Associated with Big Data**

Tools of BDA: Concerning the analytics tools used for big data, most participants used Google Analytics (35%), then SAP business intelligence platforms (18%), Apache Cassandra (15%), A-Apache Spark on Hadoop (10%), and Mongo DB (7%), among others. Whereas 15% were using some other tools for BD analytics, see Figure 5.10.

Table 5.10. Tools of BDA

Big Data Analytics Tools Used	Frequency	Percentage
Google Analytics	94	35%
SAP business intelligence platforms	49	18%
Apache Cassandra	41	15%
Apache Spark On Hadoop	27	10%
Mango DB	18	7%
Other	41	15%
Total	**270**	**100%**

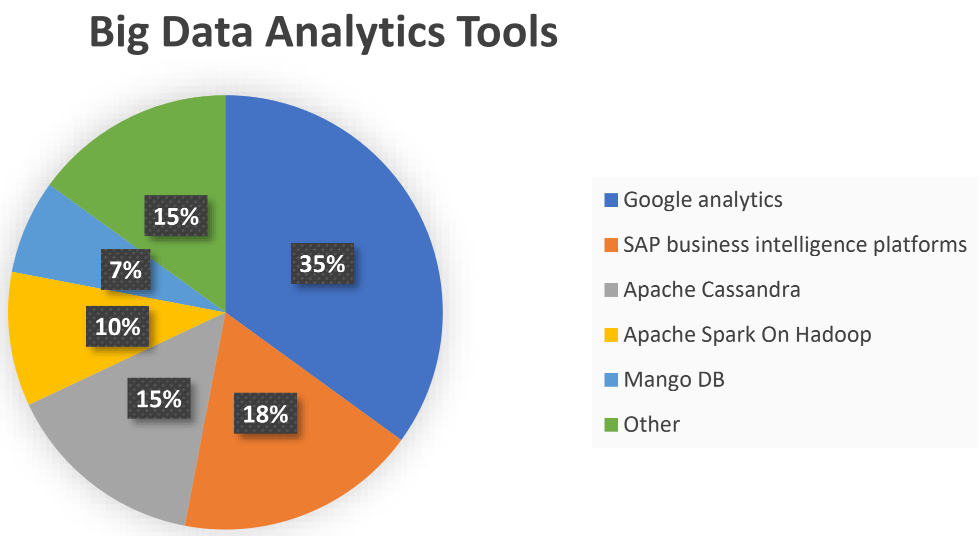

Figure 5.10. **Big Data Analytics Tools**

Common Decisions Supported by Big Data Analytics: As shown in the table and Figure 5.11, many participants have used big data to support strategic decisions (35%). It also supports performance decisions (26%), academic decisions (20%), and financial decisions (6%). In comparison, people have been using it for miscellaneous decisions (13%).

Table 5.11. Common Decisions Supported by Big Data Analytics

Common Decisions Supported by Big Data	Frequency	Percentage
Strategic Decisions	95	35%
Decisions Related to improving the performance	70	26%
Academic Decisions	54	20%
Other	35	13%
Financial Decisions	16	6%
Total	**270**	**100%**

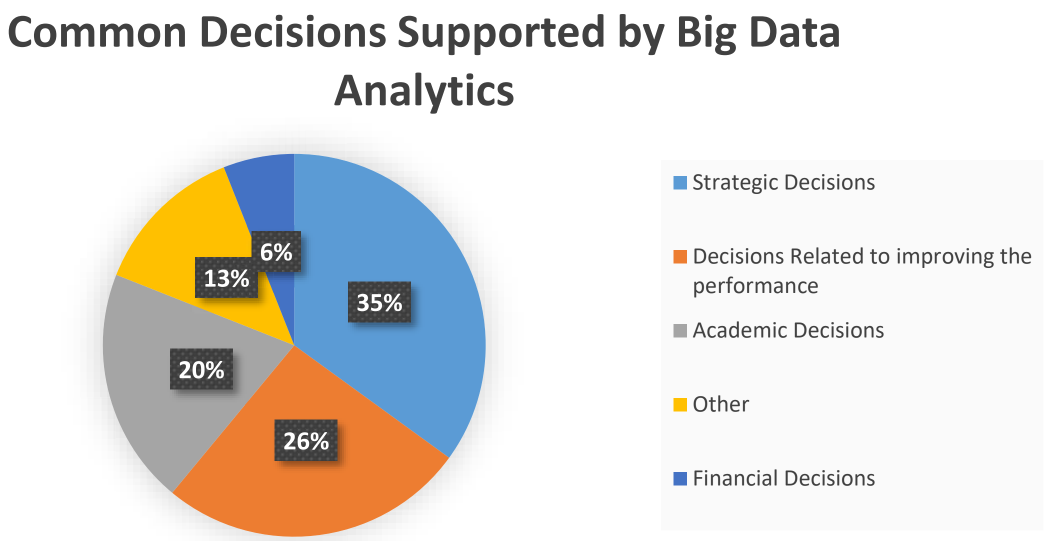

Figure 5.11. **Tools Used for Big Data Analytics**

5.3. Mean, Standard Deviation and Correlations among All Variables of the Study

In this section, we analysed the correlation between all constructs to observe the nature of the relationships between them. The correlation values are indicated in the Table below.

Table 5.14. Mean, SD and Correlations among All Variables of the Study

	M	SD	ITS	DAS	OC	ACC	ADA	BDS	PRI	QUA	SEC	BDT	STO	ANA	VIS	DES	OP
BDP	4.23	0.55															
ITS	4.27	0.57	1														
DAS	4.20	0.69	.511**	1													
OC	4.06	0.69	.362**	.271**	1												
ACC	4.14	0.74	.373**	.308**	.856**	1											
ADA	3.98	0.84	.267**	.176**	.891**	.529**	1										
BDS	4.24	0.55	.382**	.167**	.229**	.253**	.155*	1									
PRI	4.11	0.82	.292**	0.119	.179**	.204**	0.114	.855**	1								
QUA	4.24	0.63	.295**	.158**	.171**	.206**	0.099	.831**	.540**	1							
SEC	4.37	0.55	.368**	.140*	.222**	.213**	.178**	.762**	.446**	.533**	1						
BDT	3.92	0.65	.298**	.234**	.247**	.168**	.258**	.227**	.175**	.160**	.235**	1					
STO	3.77	0.94	.291**	.194**	.184**	0.110	.207**	.225**	.258**	.129*	.141*	.749**	1				
ANA	3.98	0.80	.184**	.189**	.227**	.173**	.222**	.143*	0.070	.126*	.179**	.808**	.319**	1			
VIS	4.02	0.73	.218**	.164**	.170**	0.117	.176**	.156*	0.055	.120*	.247**	.810**	.350**	.644**	1		
DES	4.34	0.56	.268**	.248**	.190**	.215**	.124*	.445**	.397**	.398**	.283**	.388**	.356**	.273**	.274**	1	
OP	4.16	0.68	.315**	.219**	.359**	.330**	.301**	.333**	.307**	.252**	.247**	.295**	.316**	.184**	.176**	.425**	1
N = 270, **p < .01, *p < .05																	

Considering the variables in Table 5.14, the strongest correlation is between analysing and visualising big data (r = .644); between privacy and quality (r = .540); the security and quality (r = .533); between adapting and accepting (r = .530); between BDS and DM (r = .445); and between big data enabled decision making and organisational performance (r = .425). Regarding other constructs, there are three constructs that represent the human element in our model – i.e., IT staff, data scientists, and organisational culture. IT staff are moderately correlated with big data storing (r = .291) and big data security (r = .368). IT staff are moderately correlated with organisational culture (r = .362), visualising big data (r = .218), and organisational performance (r = .315). Data scientists are moderately correlated with organisational culture (r = .271) and moderately correlated with analysing big data (r = .189). Similarly, organisational culture is moderately correlated with analysing big data (r = .227). Finally, organisational culture is moderately correlated with visualising (r = .170) and storing (r = .184).

The technical element in our model is represented by big data system quality and big data tasks. Big data system quality includes securing big data, maintaining privacy, and ensuring the quality of big data, whereas big data tasks include storing, analysing, and visualising big data. As earlier indicated, big data quality strongly correlates with privacy (r = .540), big data security (r = .533), and IT staff. Analysing big data is strongly correlated with visualising (r = .644) and moderately related with data scientists (r = .189). Storing big data is moderately correlated with IT staff (r = .291) and organisational culture (r = .362). Visualising big data is moderately correlated to all human aspects in the model, i.e., IT staff (r = .218), data scientists (r = .164), and organisational culture (r = .170).

We examined big data-enabled decision-making and organisational performance as outcome variables. Organisational performance is moderately correlated with decision-making (r = .425) and moderately correlated with IT staff (r = .315), big data privacy (r = .307), and big data quality (r = .252). Decision-making is moderately correlated with big data quality (r = .398) and moderately correlated with big data privacy (r = .397). On the other hand, there is a very small correlation between analysing big data and big data privacy (r = .070) and between privacy and visualising big data (r = .055).

5.4 Descriptive Analysis of Measurement Scales

We will cover the study scales' frequencies and percentages in the following section of this chapter. All the scales were measured on 5-point Likert scales, and descriptive details will cover the scales on item levels.

5.4.1 Big Data Analytics Performance

This scale has two parts, i.e., IT Staff and Data Scientists. Each of them is described below separately.

IT Staff: Table 5.15 and Figure 5.12 show the percentages and frequencies on ITS1; we can note that the majority of the participants (n = 250) strongly concurred with the statement of this item.

Table 5.15. ITS1 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	1	.4
	DA	2	.7
	N	17	6.3
	AG	98	36.3
	SA	152	56.3
	Total	270	100.0
SD: "Strongly Disagree". **DA:** "Disagree". **N:** "Neutral" **AG:** "Agree" **SA:** "Strongly Agree"			

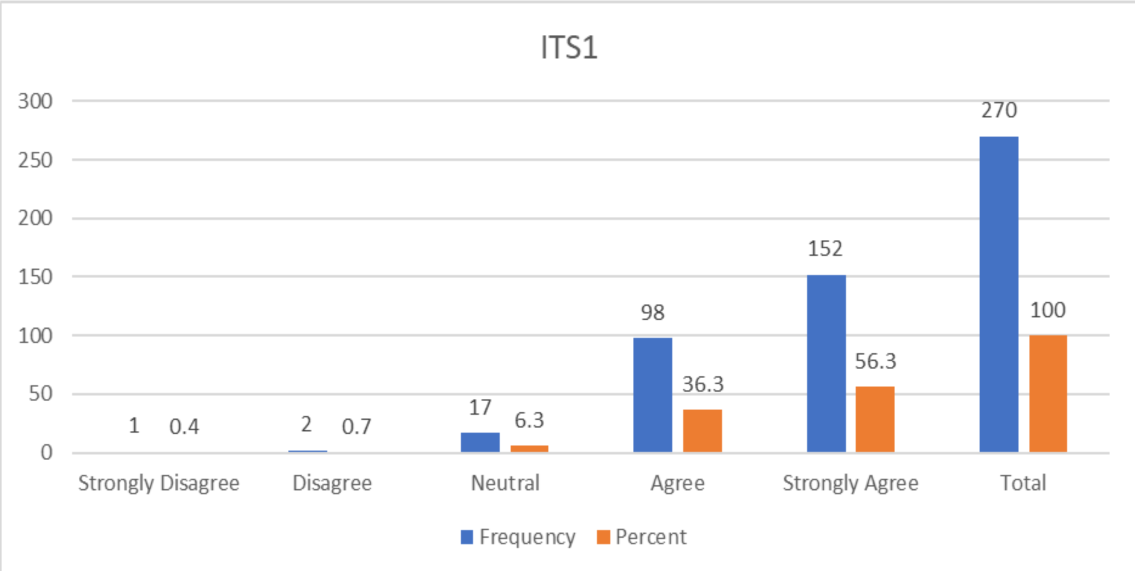

Figure 5.12. **ITS1 Descriptive Graph**

Table 5.16 and Figure 5.13 show the percentages and frequencies of ITS2, and we can note that majority (n = 237) of the participants "strongly concurred" with the statement of this item.

Table 5.16. ITS2 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	1	.4
	DA	2	.7

	N	35	13.0
	AG	127	47.0
	SA	105	38.9
	Total	270	100.0

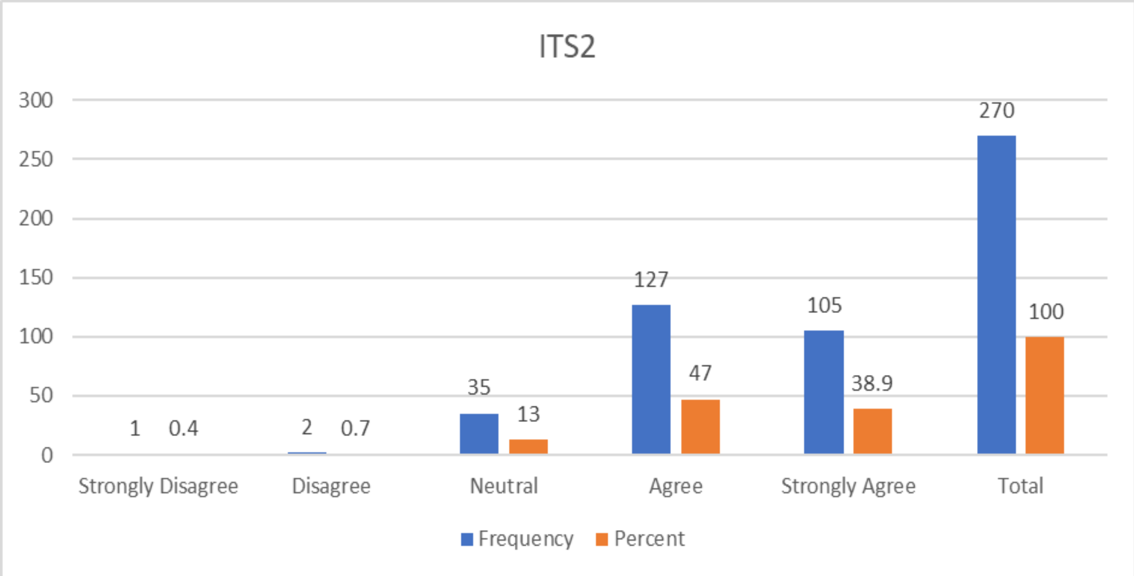

Figure 5.13. **ITS2 Descriptive Graph**

Table 5.17 and Figure 5.14 show the percentages and frequencies on ITS3, and we can note that majority (n = 232) of the respondents "strongly concurred" with the statement of this item.

Table 5.17. ITS3 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	1	.4
	DA	2	.7
	N	35	13.0
	AG	127	47.0
	SA	105	38.9
	Total	270	100.0

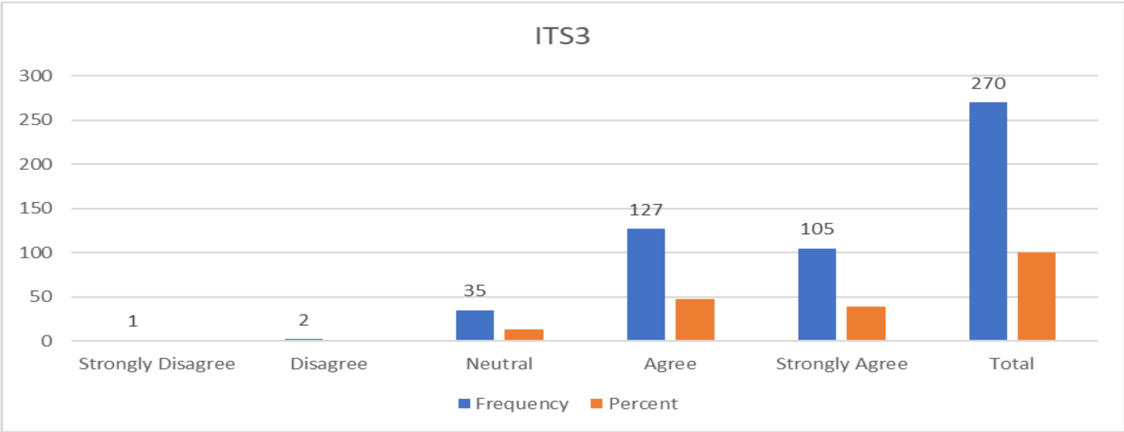

Figure 5.14. **ITS3 Descriptive Graph**

Table 5.18 and Figure 5.15 show the percentages and frequencies on ITS4, and we can note that majority (n = 226) of the respondents "strongly concurred" with the statement of this item.

Table 5.18. ITS4 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	1	.4
	DA	2	.7
	N	41	15.2
	AG	125	46.3
	SA	101	37.4
	Total	270	100.0

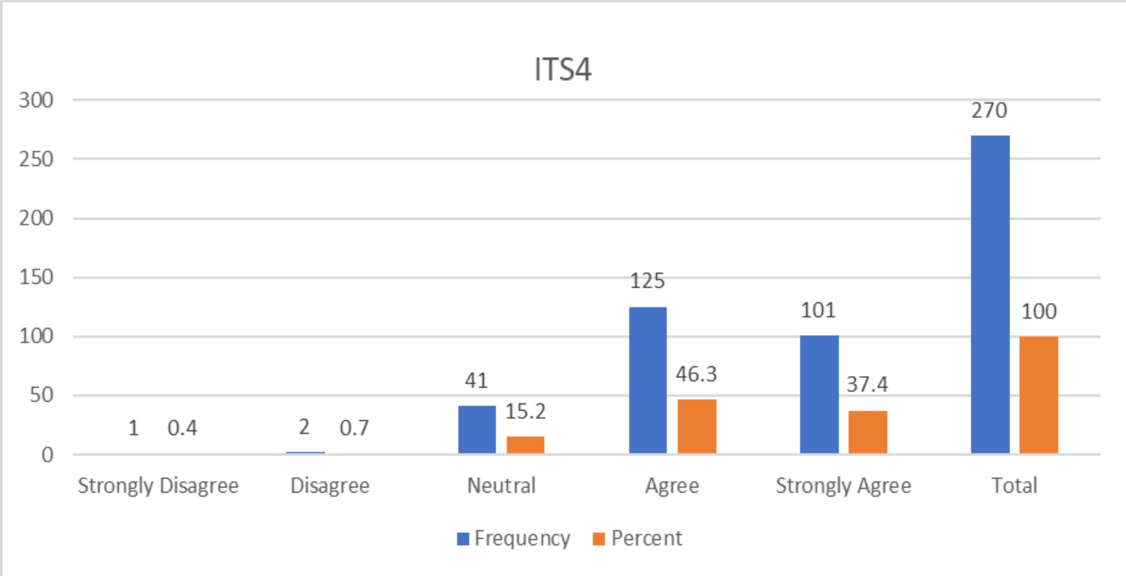

Figure 5.15. **ITS4 Descriptive Graph**

Table 5.19 and Figure 5.16 show the percentages and frequencies on ITS5, and we can note that majority (n = 233) of the respondents "strongly concurred" with the statement of this item.

Table 5.19. ITS5 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	1	.4
	DA	2	.7
	N	34	12.6
	AG	135	50.0
	SA	98	36.3
	Total	270	100.0

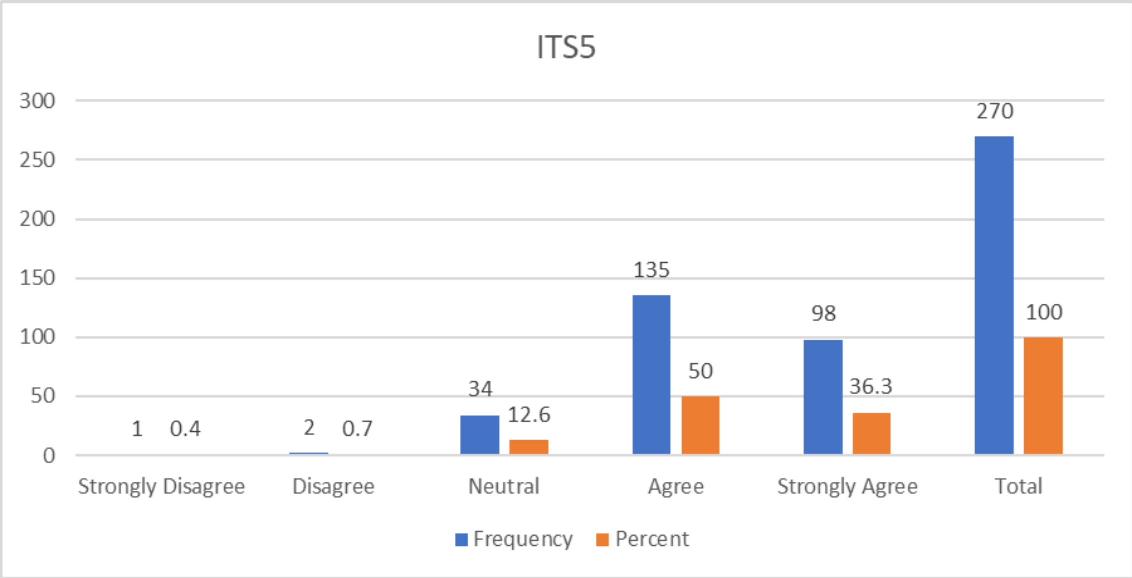

Figure 5.16. **ITS5 Descriptive Graph**

Table 5.20 and Figure 5.17 show the percentages and frequencies on ITS6, and we can note that majority (n = 238) of the participants "strongly concurred" agreed with the statement of this item.

Table 5.20. ITS6 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	1	.4
	DA	2	.7
	N	29	10.7
	AG	132	48.9
	SA	106	39.3
	Total	270	100.0

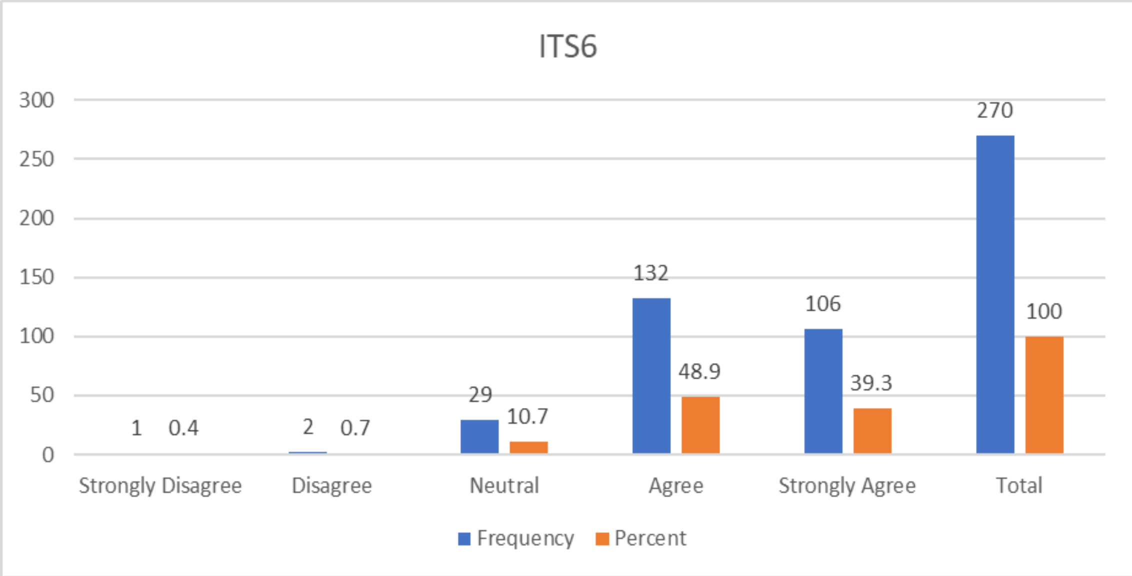

Figure 5.17. **ITS6 Descriptive Graph**

Data Scientists: Table 5.21 and Figure 5.18 show the percentages and frequencies on DAS1; we can note that majority of the participants (n = 236) "strongly concurred" with DAS1 statement.

Table 5.21. DAS1 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	2	.7
	DA	8	3.0
	N	24	8.9
	AG	137	50.7
	SA	99	36.7
	Total	270	100.0

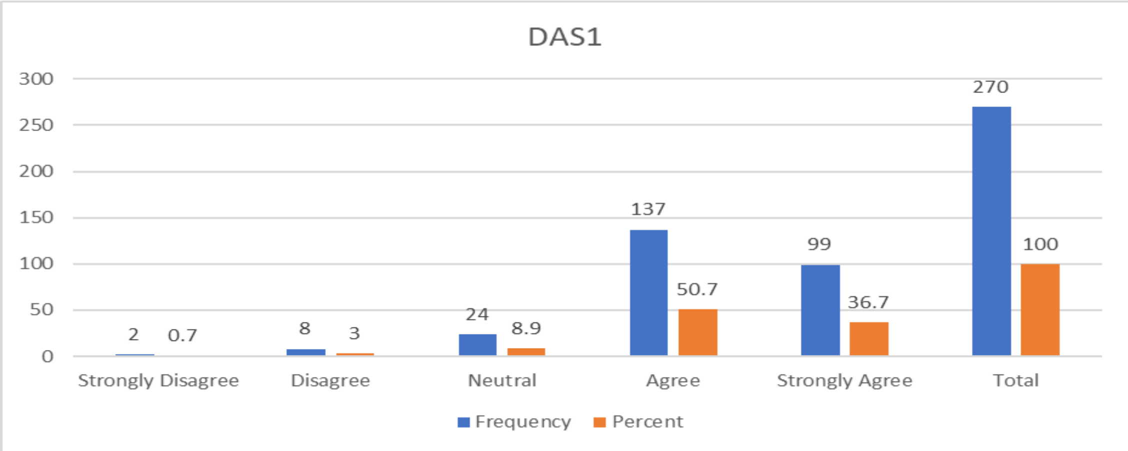

Figure 5.18. **DAS1 Descriptive Graph**

Table 5.22 and Figure 5.19 show the percentages and frequencies on DAS2; we can note that majority of the participants (n = 232) "strongly concurred" with the statement of this item.

Table 5.22. DAS2 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	2	.7
	DA	4	1.5
	N	32	11.9
	AG	129	47.8
	SA	103	38.1
	Total	270	100.0

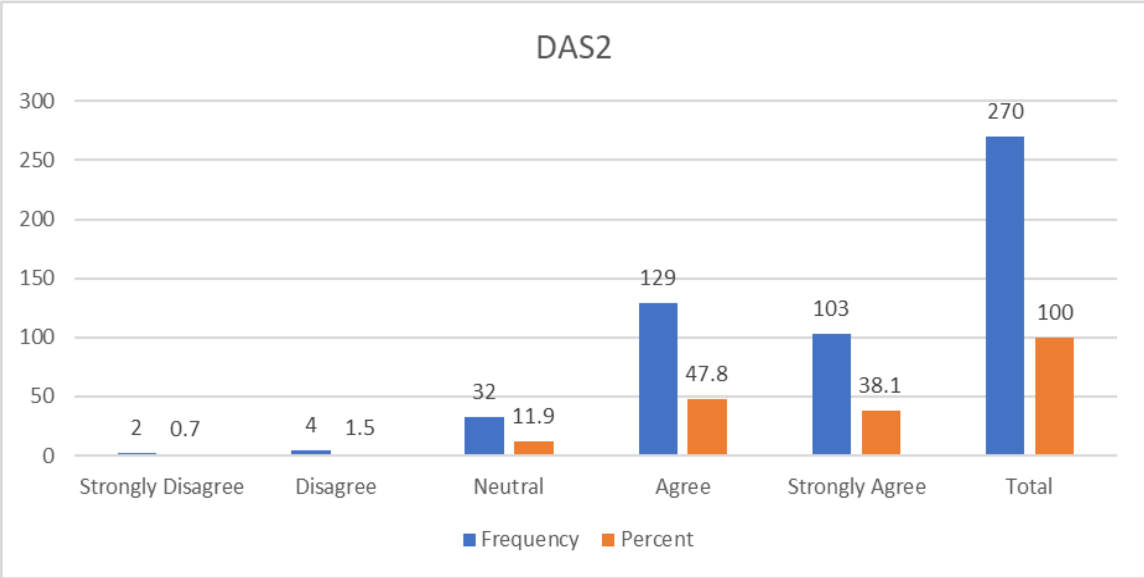

Figure 5.19. **DAS2 Descriptive Graph**

Table 5.23 and Figure 5.20 show the percentages and frequencies on DAS3; we can note that majority of the participants (n = 235) "strongly concurred" with the statement of this item.

Table 5.23. DAS3 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	1	.4
	DA	6	2.2
	N	28	10.4
	AG	142	52.6
	SA	93	34.4
	Total	270	100.0

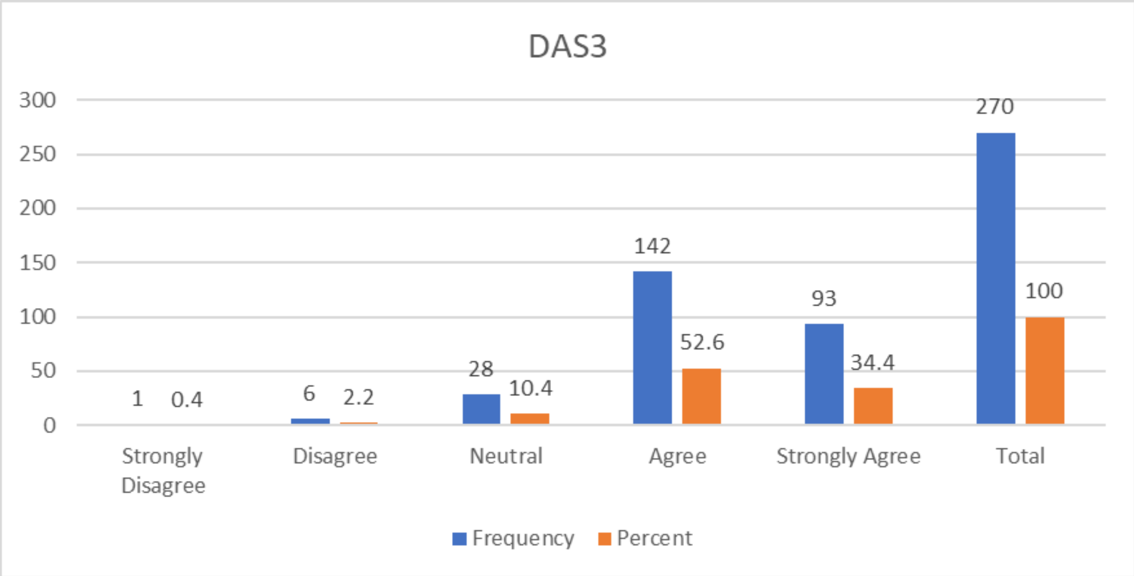

Figure 5. 20. DAS3 Descriptive Graph

5.4.2 Organisational Culture OC

This scale has two parts, i.e., Accepting (ACC) to Big Data technological improvements and Adapting (ADA) to Big Data Technological enhancements. Each of them is described below separately.

Accepting: Table 5.24 and Figure 5.21 show the percentages and frequencies on ACC1; we can note that majority of the respondents (n = 230) "strongly concurred" with ACC1 statement.

Table 5.24. ACC1 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	2	.7
	DS	16	5.9
	N	22	8.1
	AG	104	38.5
	SA	126	46.7

	Total	270	100.0

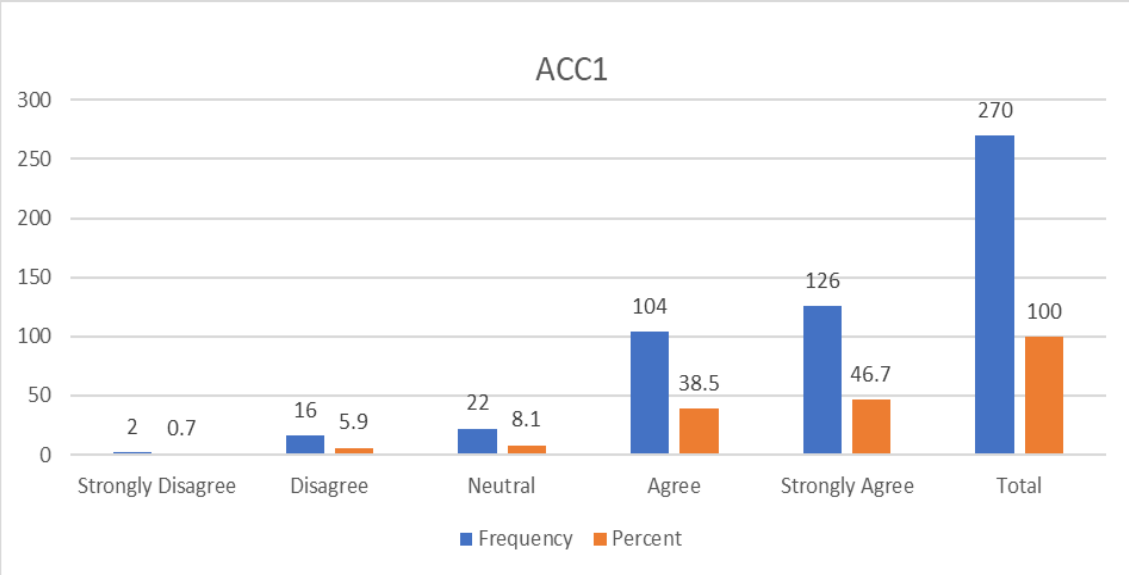

Figure 5.21. **ACC1 Descriptive Graph**

Table 5.25 and Figure 5.22 show the percentages and frequencies on ACC2; we can note that majority of the respondents (n = 220) "strongly concurred" with the statement of ACC2.

Table 5.25. ACC2 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	3	1.1
	DA	14	5.2
	N	33	12.2
	AG	119	44.1
	SA	101	37.4
	Total	270	100.0

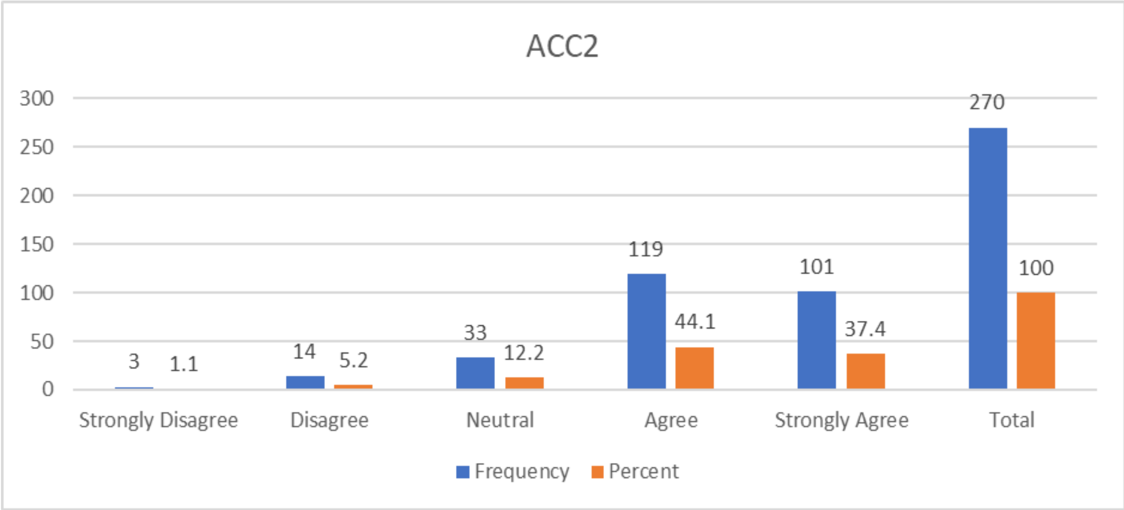

Figure 5.22. **ACC2 Descriptive Graph**

Table 5.26 and Figure 5.23 show the percentages and frequencies on ACC3; we can note that majority of the participants (n = 226) "strongly concurred" with the statement of ACC3.

Table 5.26. ACC3 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	9	3.3
	DA	13	4.8
	N	22	8.1
	AG	135	50.0
	SA	91	33.7
	Total	270	100.0

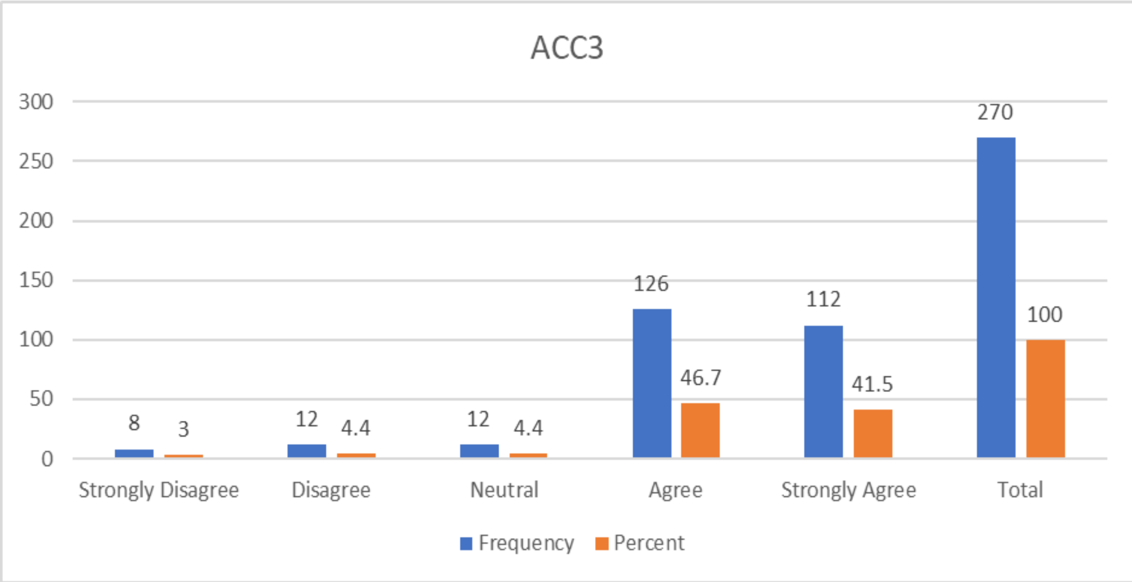

Figure 5.23. **ACC3 Descriptive Graph**

Adapting: Table 5.27 and Figure 5.24 show the percentages and frequencies on ADA1, we can note that majority of the participants (n = 202) "strongly concurred" with ADA1 statement.

Table 5.27. ADA1 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	7	2.6
	DA	22	8.1
	N	39	14.4
	A	105	38.9
	SA	97	35.9
	Total	270	100.0

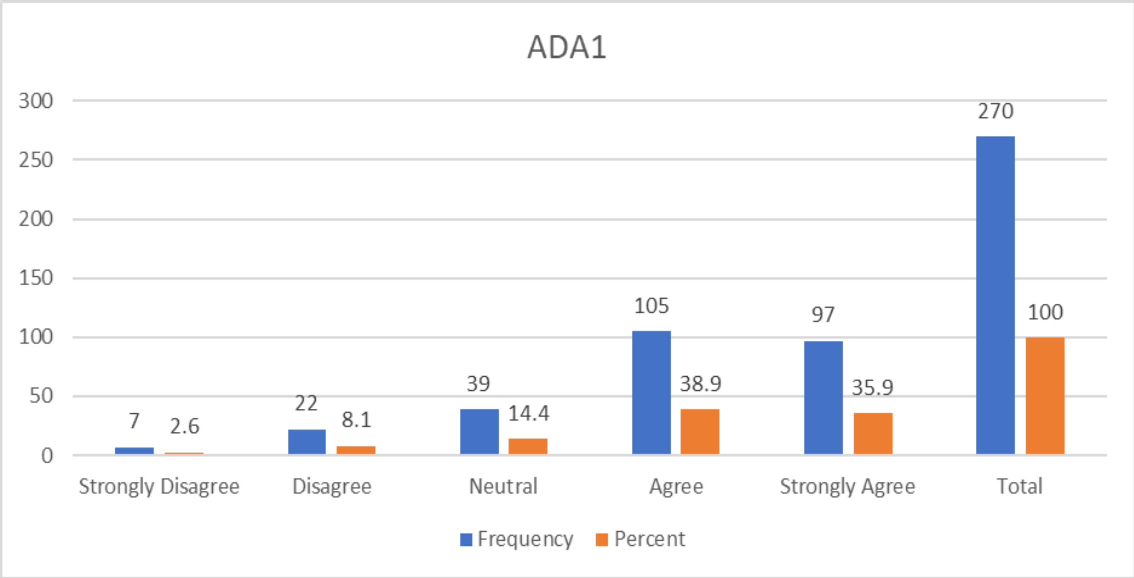

Figure 5.24. **ADA1 Descriptive Graph**

Table 5.28 and Figure 5.25 show the percentages and frequencies on ADA2; we can note that majority of the respondents (n = 206) "strongly concurred" with ADA2 statement.

Table 5.28. ADA2 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	9	3.3
	DA	17	6.3
	N	38	14.1
	AG	106	39.3
	SA	100	37.0
	Total	270	100.0

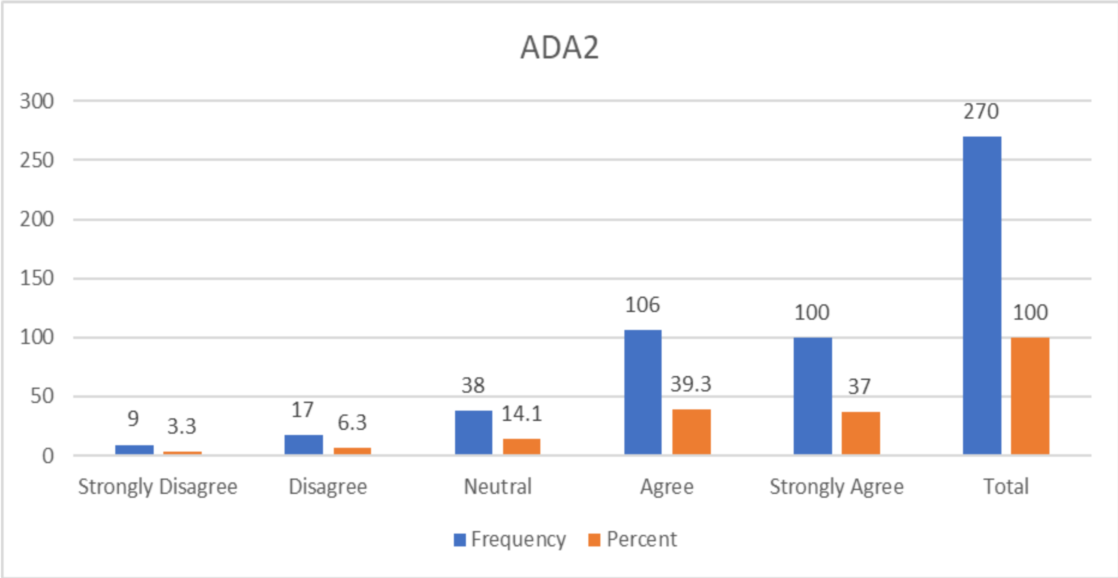

Figure 5.25. **ADA2 Descriptive Graph**

Figure 5.26 and Table 5.29 show the percentages and frequencies on ADA3; we can note that majority of the participants (n = 208) "strongly concurred" with ADA3 statement.

Table 5.29. ADA3 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	7	2.6
	DA	19	7.0
	N	36	13.3
	AG	120	44.4
	SA	88	32.6
	Total	270	100.0

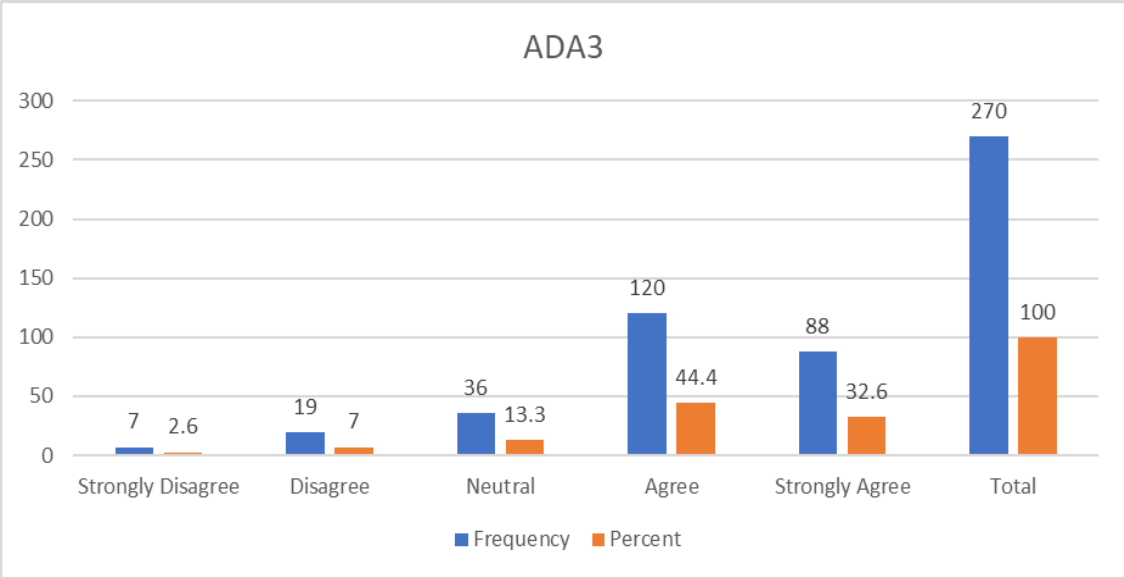

Figure 5.26. ADA3 Descriptive Graph

5.4.3 Big Data System Quality

BDAS scale has three aspects, i.e., Security (SEC), Privacy (PRI) and Quality (QUA), all of such factors are described below separately.

Security: Table 5.30 and Figure 5.27 show the percentages and frequencies on SEC1; we can note that most participants (n = 249) "strongly concurred" with the SEC1 statement.

Table 5.30. SEC1 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	1	.4
	DA	1	.4
	N	20	7.4
	AG	65	24.1
	SA	184	64.1
	Total	270	100.0

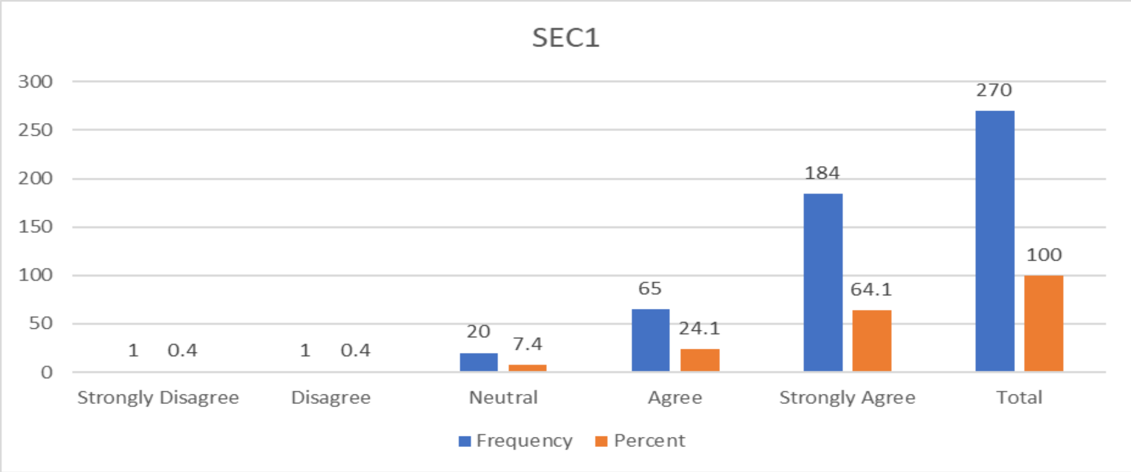

Figure 5.27. **SEC1 Descriptive Graph**

Table 5.31 and Figure 5.28 show the percentages and frequencies on SEC2; we can note that majority of the participants (n = 246) "strongly concurred" with SEC2 statement.

Table 5.31. SEC2 – Descriptive Analysis

Statement		Frequency	Percent
Valid	DA	3	1.1
	N	21	7.8
	AG	140	51.9
	SA	106	39.3
	Total	270	100.0

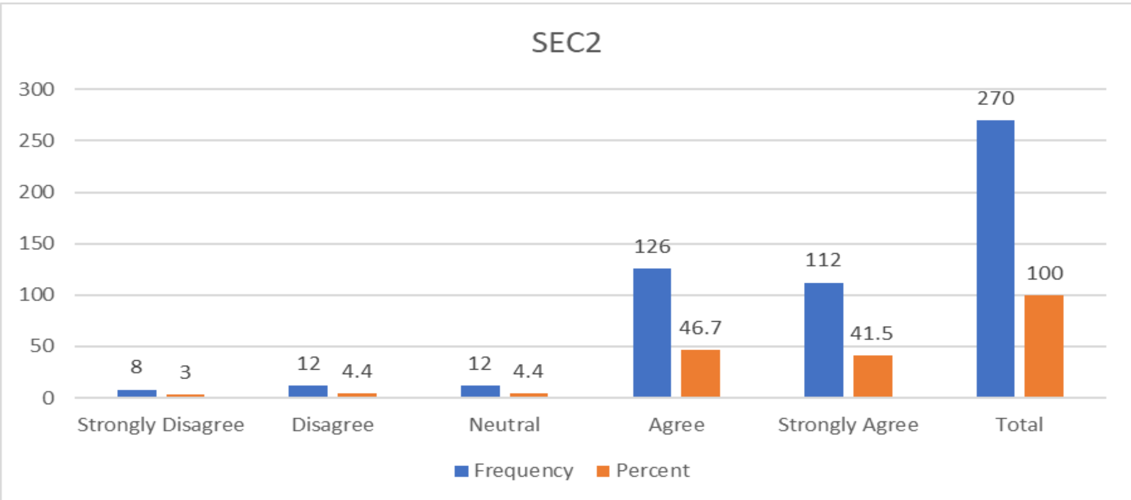

Figure 5.28. **SEC2 Descriptive Graph**

Table 5.32 and Figure 5.29 show the percentages and frequencies on SEC3; we can note that most participants (n = 246) "strongly concurred" with the SEC3 statement.

Table 5.32. SEC3 – Descriptive Analysis

Statement		Frequency	Percent
Valid	DA	2	.7
	N	22	8.1
	AG	157	58.1
	SA	89	33.0
	Total	270	100.0

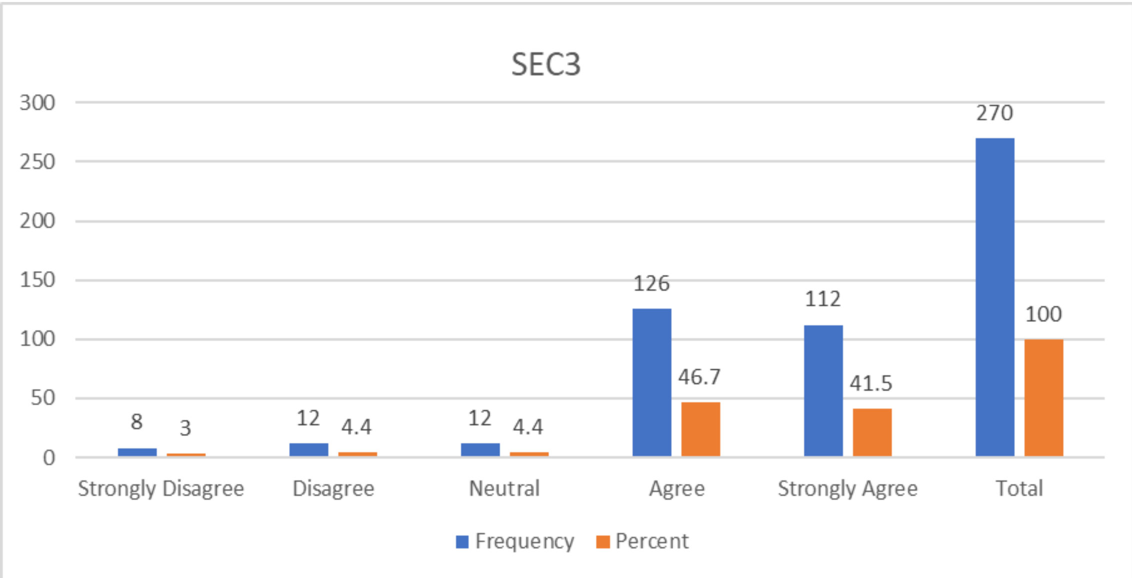

Figure 5.29. **SEC3 Descriptive Graph**

Privacy: Table 5.33and Figure 5.30 show the percentages and frequencies on PRI1; we can note that majority of the participants (n = 227) "strongly concurred" with PRI1 statement.

Table 5.33. PRI1 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	5	1.9
	DA	17	6.3
	N	21	7.8
	AG	128	47.4
	SA	99	36.7
	Total	270	100.0

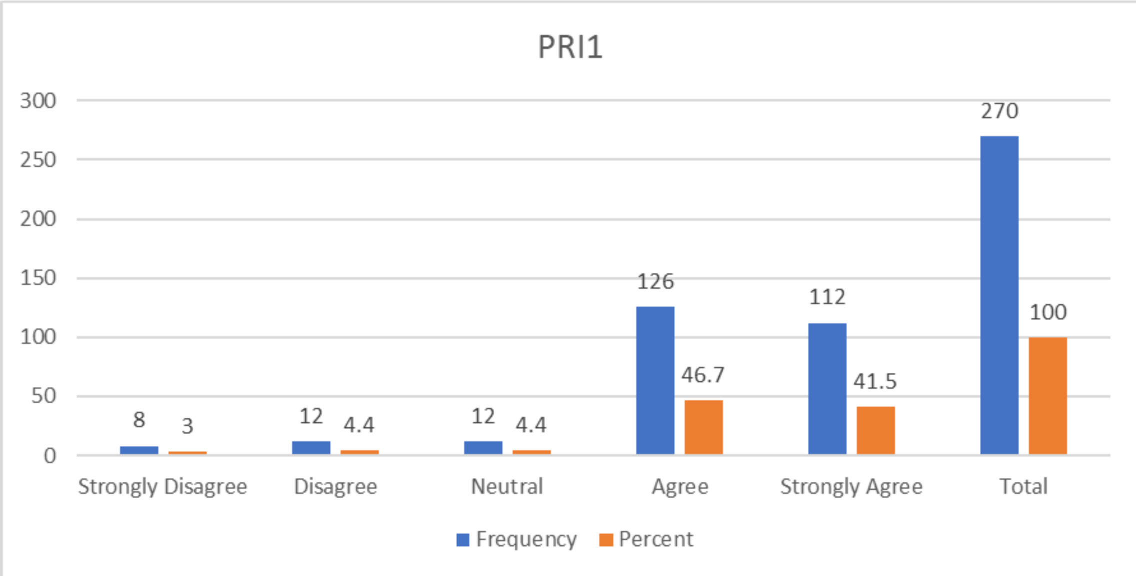

Figure 5.30. **PRI1 Descriptive Graph**

Table 5.34 and Figure 5.31 show the percentages and frequencies on PRI2; we can note that majority of the respondents (n = 218) agreed with PRI2 statement.

Table 5.34. PRI2 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	6	2.2
	DA	20	7.4
	N	26	9.6
	AG	125	46.3
	SA	93	34.4

	Total	270	100.0

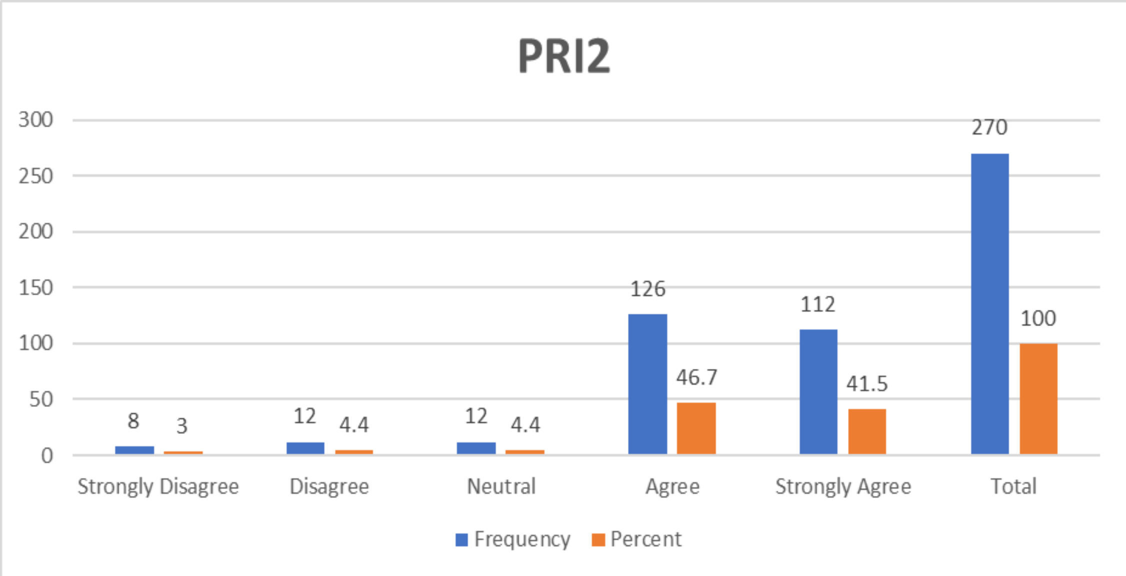

Figure 5.31. **PRI2 Descriptive Graph**

Table 5.35 and Figure 5.32 show the percentages and frequencies on PRI3; we can note that majority of the respondents (n = 230) "strongly concurred" with PRI3 statement.

Table 5.35. PRI3 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	4	1.5
	DA	12	4.4
	N	24	8.9
	AG	116	43.0
	SA	114	42.2
	Total	270	100.0

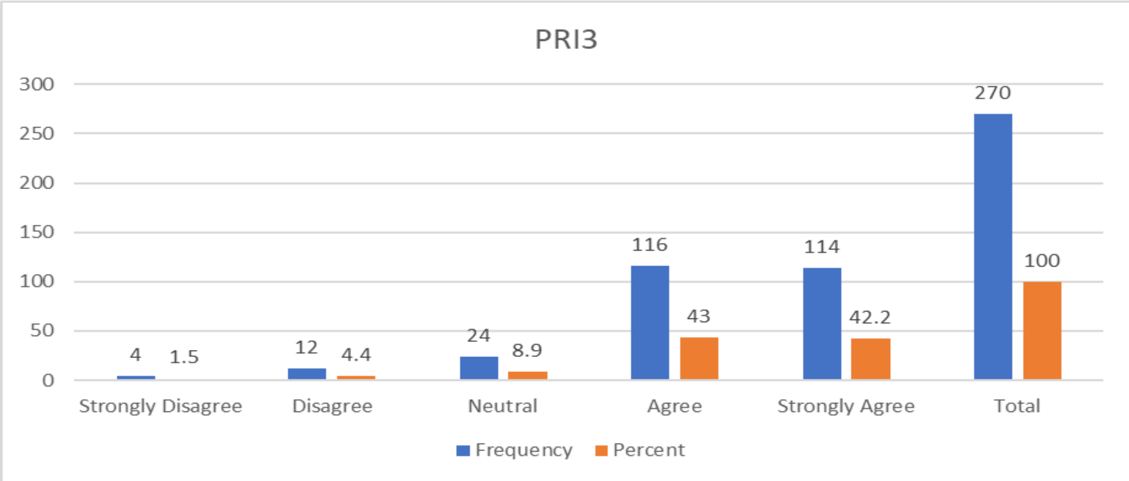

Figure 5.32. **PRI3 Descriptive Graph**

Big Data Quality QUA: Table 5.36 and Figure 5.33 show the percentages and frequencies on QUA1; we can note that most participants (n = 235) "strongly concurred" with the QUA1 statement.

Table 5.36. QUA1 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	1	.4
	DA	4	1.5
	N	30	11.1
	AG	129	47.8
	SA	106	39.3
	Total	270	100.0

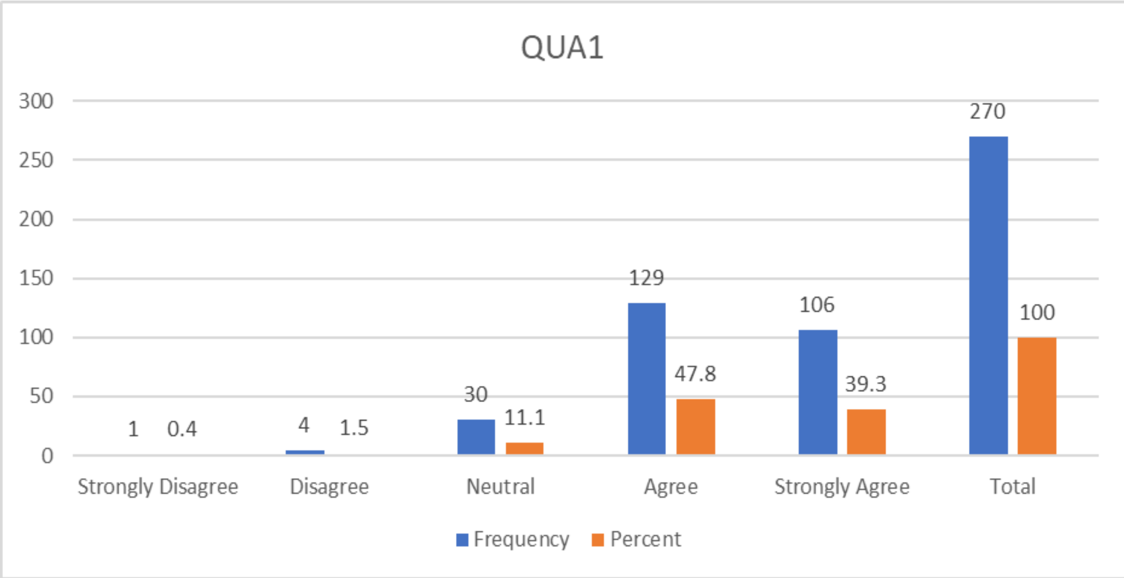

Figure 5.33. **QUA1 Descriptive Graph**

Table 5.37 and Figure 5.34 show the percentages and frequencies on QUA2; we can note that most participants (n = 241) "strongly concurred" with the QUA2 statement.

Table 5.37. QUA2 – Descriptive Analysis

Statement		Frequency	Percent
Valid	DA	4	1.5
	N	25	9.3
	AG	133	49.3
	SA	108	40.0
	Total	270	100.0

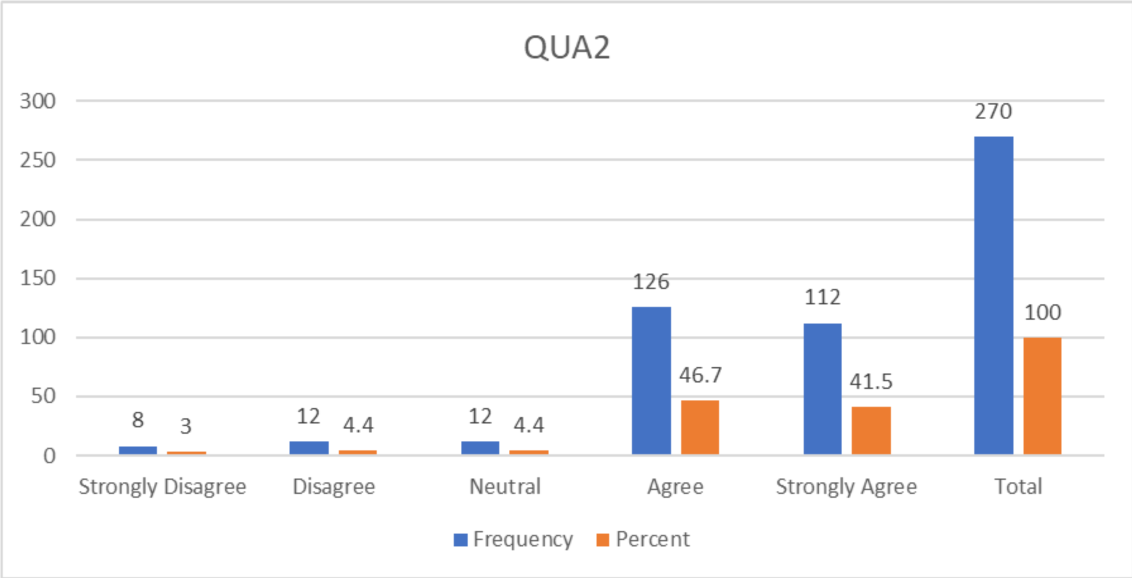

Figure 5.34. **QUA2 Descriptive Graph**

Table 5.38 and Figure 5.35 show the percentages and frequencies on QUA3; we can note that majority of the participants (n = 240) "strongly concurred" with the QUA3 statement.

Table 5.38. QUA3 – Descriptive Analysis

Statement		Frequency	Percent
Valid	DA	6	2.2
	N	24	8.9
	AG	150	55.6
	SA	90	33.3
	Total	270	100.0

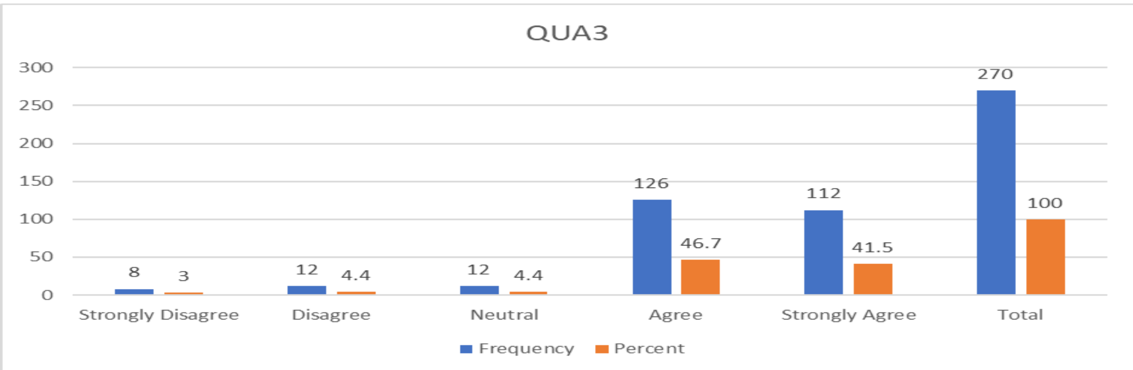

Figure 5.35. **QUA3 Descriptive Graph**

5.4.4 Big Data Tasks BDT

The BDT scale has three parts, i.e., storing data from various resources (STO), Analysing those stored data (ANA) and Visualising analysed data for improving the decisions of executives in Saudi HEIs (VIS). Each of them is described below separately.

Storing: Table 5.39 and Figure 5.36 show the percentages and frequencies of STO1; we can note that majority of the participants (n = 198) "strongly concurred" with STO1 statement.

Table 5.39. STO1 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	15	5.6
	DA	20	7.4
	N	37	13.7
	AG	124	45.9
	SA	74	27.4
	Total	270	100.0

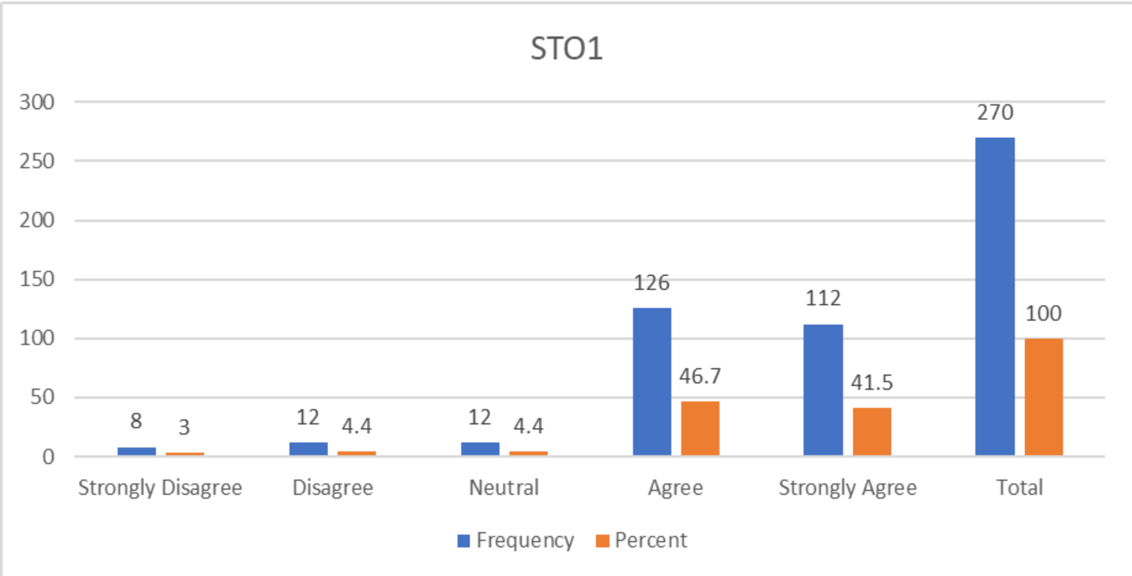

Figure 5.36. **STO1 Descriptive Graph**

Table 5.40 and Figure 5.37 show the percentages and frequencies on STO2; we can note that majority of the participants (n = 180) agreed with STO2 statement.

Table 5.40. STO2 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	11	4.1
	DA	24	8.9
	N	55	20.4
	AG	114	42.2
	SA	66	24.4
	Total	270	100.0

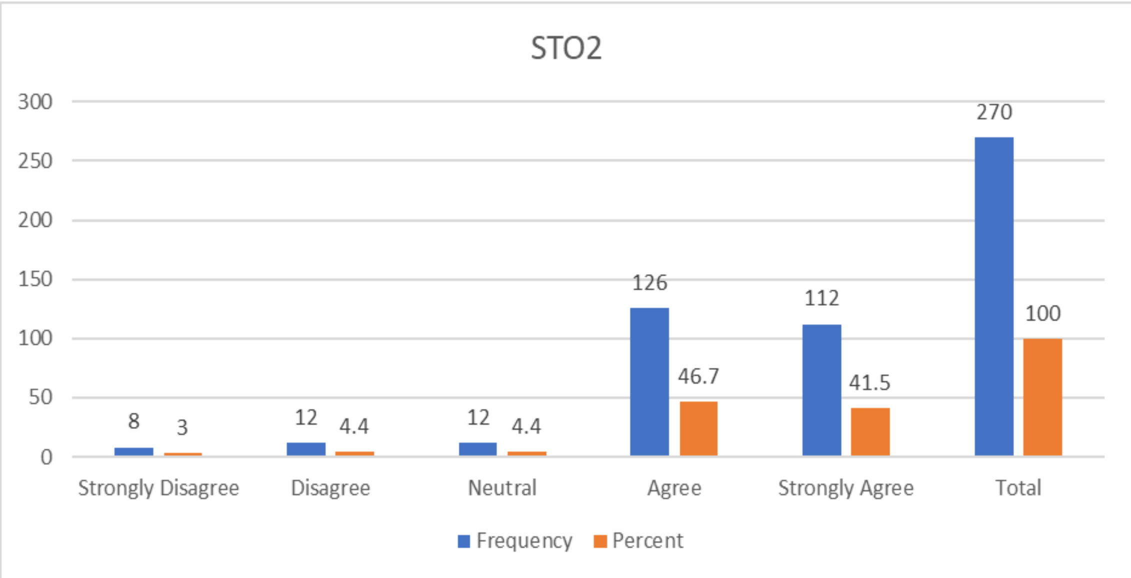

Figure 5.37. **STO2 Descriptive Graph**

Table 5.41 and Figure 5.38 show the percentages and frequencies on STO3; we can note that majority of the participants (n = 186) "strongly concurred" with STO3 statement.

Table 5.41. STO3 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	8	3.0
	DA	27	10.0
	N	49	18.1

	AG	130	48.1
	SA	56	20.7
	Total	270	100.0

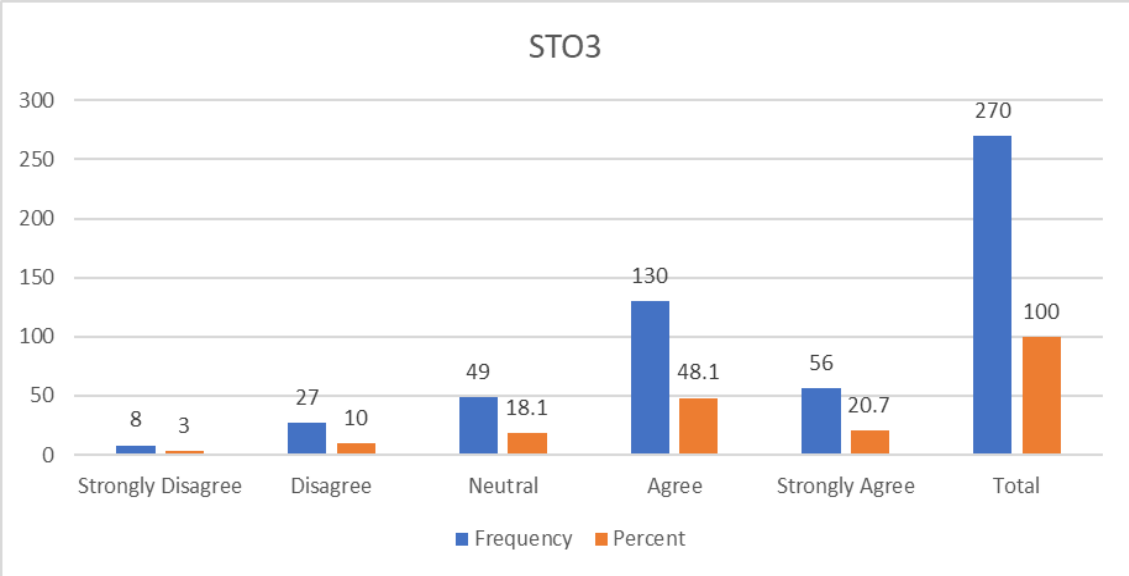

Figure 5.38. **STO3 Descriptive Graph**

Analysing: Table 5.42 and Figure 5.39 show the percentages and frequencies on ANA1; we can note that majority of the participants (n = 212) "strongly concurred" with ANA1 statement.

Table 5.42. ANA1 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	4	1.5
	DA	14	5.2
	N	40	14.8
	AG	138	51.1
	SA	74	27.4
	Total	270	100.0

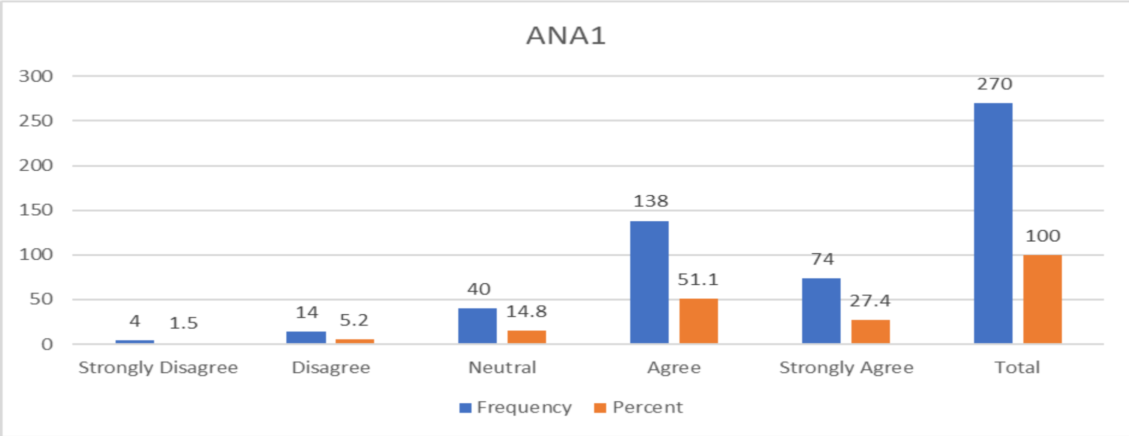

Figure 5.39. **ANA1 Descriptive Graph**

Table 5.43and Figure 5.40 show the percentages and frequencies on ANA2; we can note that majority of the participants (n = 202) "strongly concurred" with ANA2 statement.

Table 5.43. ANA2 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	5	1.9
	DA	11	4.1
	N	52	19.3
	AG	119	44.1
	SA	83	30.7
	Total	270	100.0

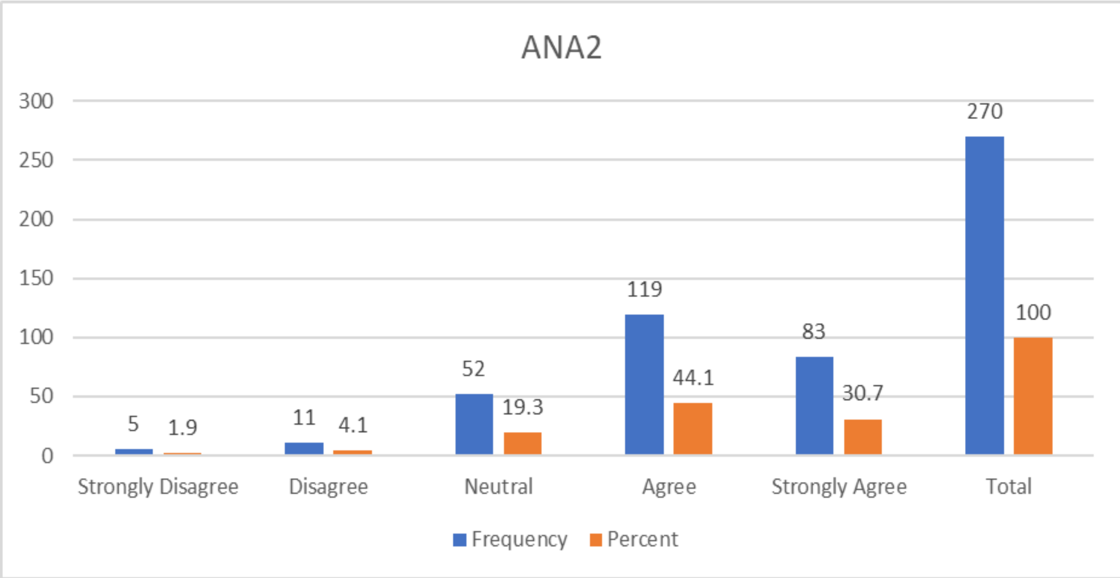

Figure 5.40. **ANA2 Descriptive Graph**

Table 5.44 and Figure 5.41 show the percentages and frequencies on ANA3; we can note that majority of the participants (n = 207) "strongly concurred" with ANA3 statement.

Table 5.44. ANA3 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	3	1.1
	DA	11	4.1
	N	49	18.1
	AG	134	49.6
	SA	73	27.0
	Total	270	100.0

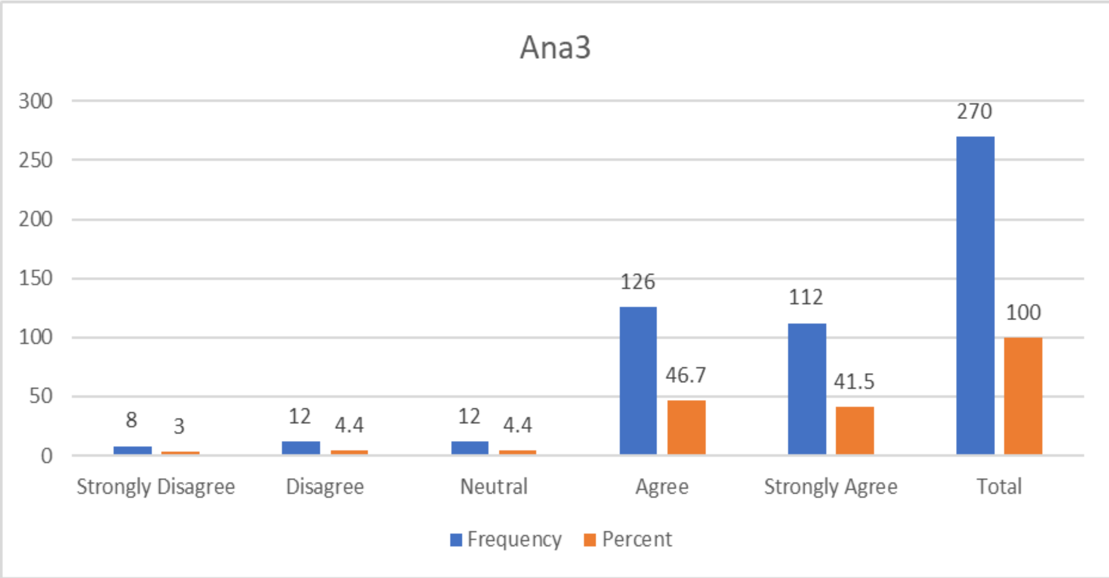

Figure 5.41. **ANA3 Descriptive Graph**

Visualising: Table 5.45 and Figure 5.42 show the percentages and frequencies on VIS1; we can note that majority of the participants (n = 213) agreed with VIS1 statement.

Table 5.45. VIS1 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	1	.4
	DA	9	3.3
	N	47	17.4
	AG	128	47.4
	SA	85	31.5
	Total	270	100.0

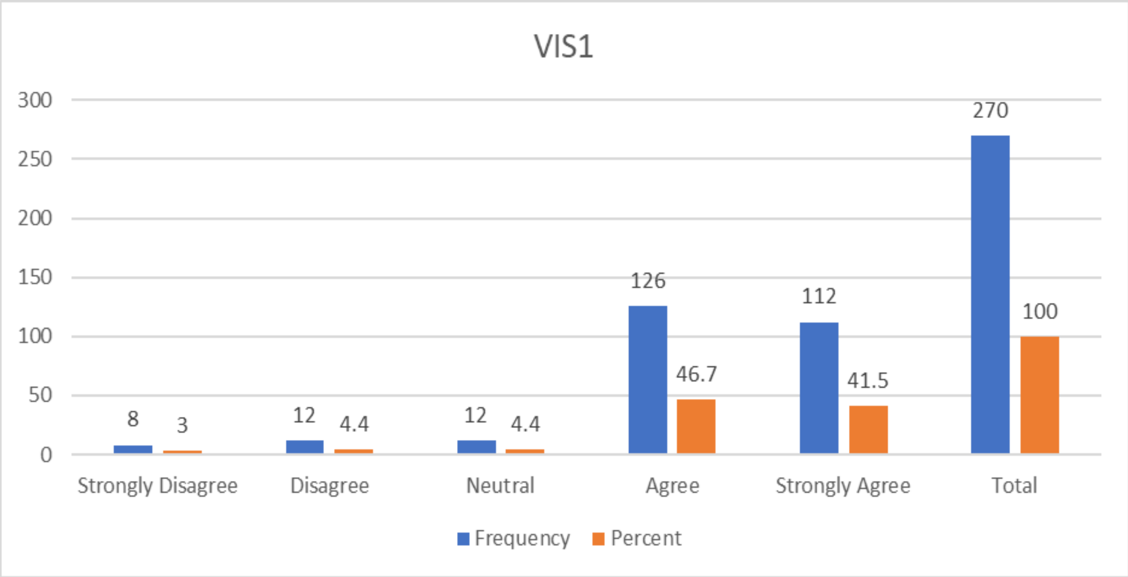

Figure 5.42. **VIS1 Descriptive Graph**

Table 5.46 and Figure 5.43 show the percentages and frequencies on VIS2; we can note that majority of the participants (n = 208) "strongly concurred" with VIS2 statement.

Table 5.46. VIS2 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	1	.4
	DA	11	4.1
	N	50	18.5
	AG	137	50.7
	SA	71	26.3
	Total	270	100.0

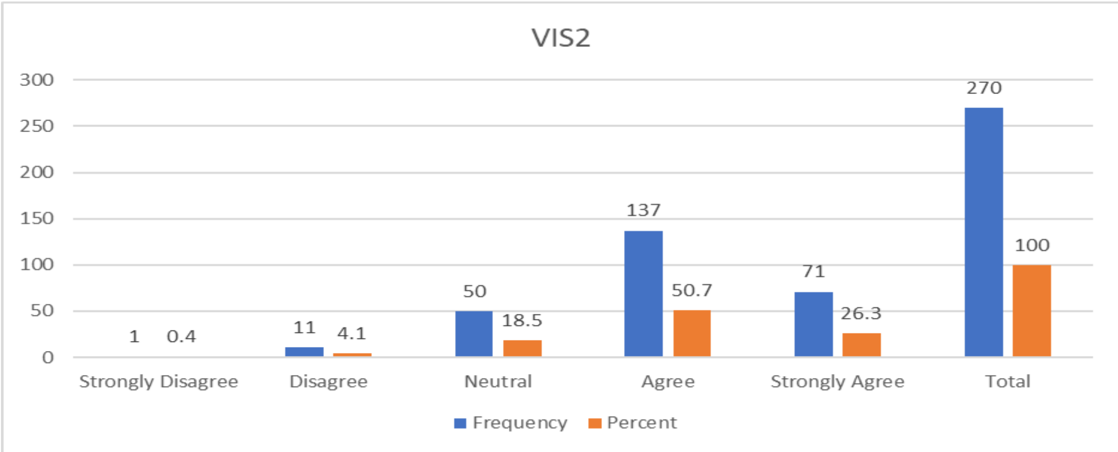

Figure 5.43. **VIS2 Descriptive Graph**

Table 5.47 and Figure 5.44 show the percentages and frequencies on VIS3; we can note that majority of the participants (n = 215) "strongly concurred" with VIS3 statement.

Table 5.47. VIS3 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	2	.7
	DA	8	3.0
	N	45	16.7
	AG	144	53.3
	SA	71	26.3
	Total	270	100.0

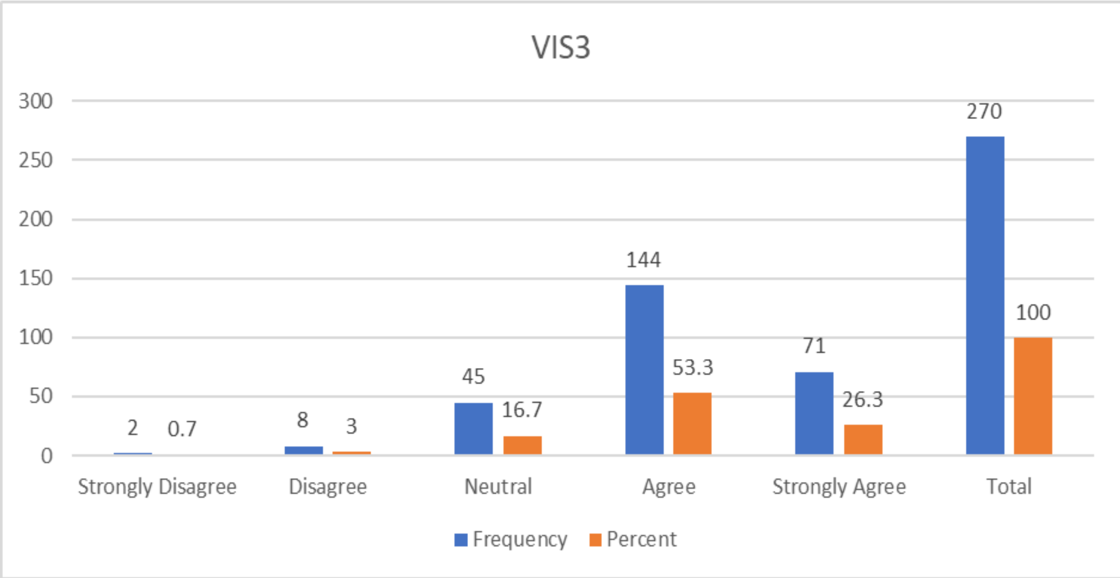

Figure 5.44. **VIS3 Descriptive Graph**

5.4.5 Improving Decision-Making DES

Table 5.48 and Figure 5.45 show the percentages and frequencies on Improving the decisions of executives in Saudi HEIs (DES1); we can note that majority of the participants (n = 250) strongly /"strongly concurred" with DES1 statement.

Table 5.48. DES1 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	2	.7
	DA	1	.4
	N	17	6.3
	AG	64	23.7
	SA	186	68.9
	Total	270	100.0

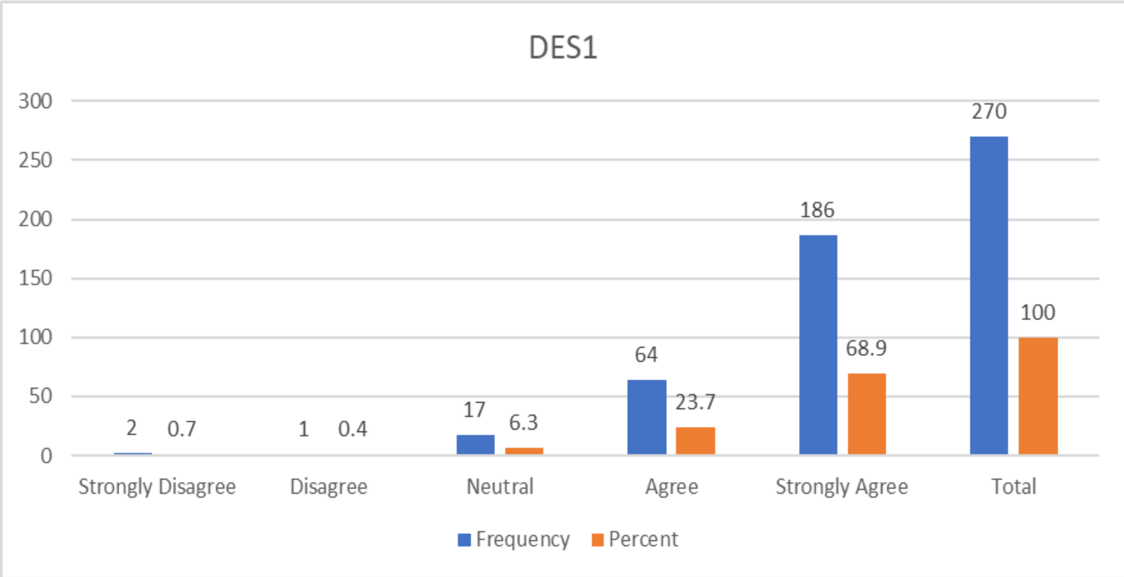

Figure 5.45. **DES1 Descriptive Graph**

Table 5.49 and Figure 5.46 show the percentages and frequencies on DES2; we can note that majority of the participants (n = 239) "strongly concurred" with the DES2 statement.

Table 5.49. DES2 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	2	.7
	DA	7	2.6
	N	22	8.1
	AG	134	49.6
	SA	105	38.9
	Total	270	100.0

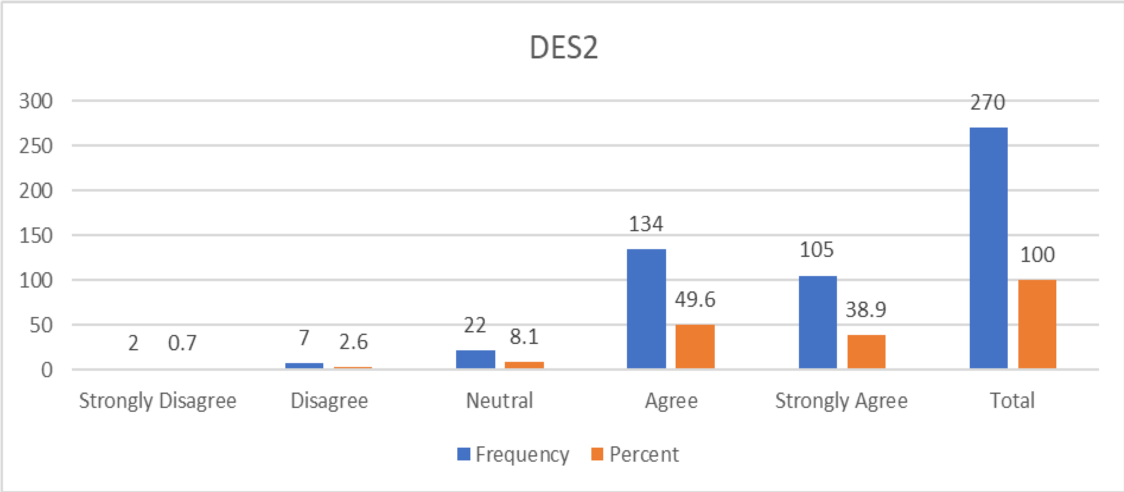

Figure 5.46. **DES2 Descriptive Graph**

Table 5.50 and Figure 5.47 show the percentages and frequencies on DES3, we can note that majority of the participants (n = 230) "strongly concurred" with DES3 statement.

Table 5.50 DES3 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	1	.4
	DA	7	2.6
	N	32	11.9
	AG	125	46.3
	SA	105	38.9
	Total	270	100.0

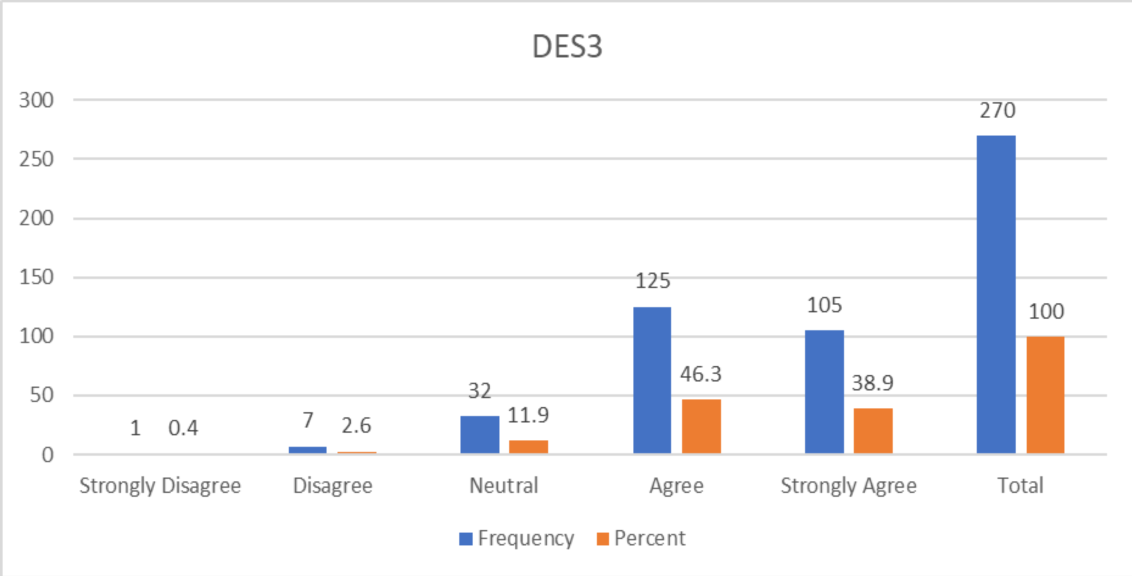

Figure 5.47. **DES3 Descriptive Graph**

Table 5.51 and Figure 5.48 show the percentages and frequencies on DES4; we can note that majority of the participants (n = 249) "strongly concurred" with DES4 statement.

Table 5.52. DES4 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	1	.4
	DA	6	2.2
	N	14	5.2
	AG	126	46.7
	SA	123	45.6
	Total	270	100.0

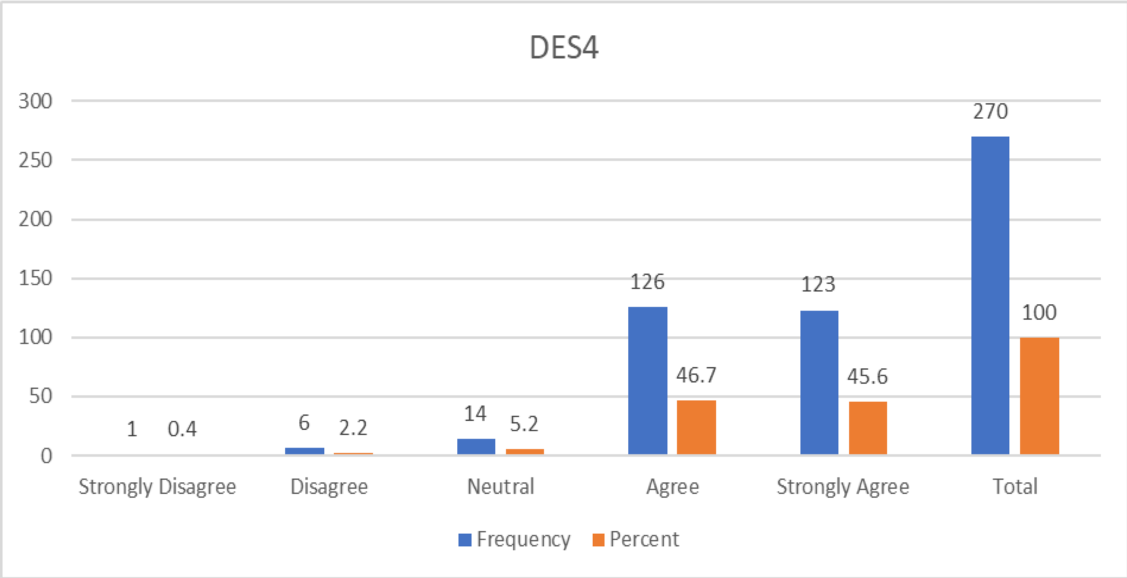

Figure 5.47. **DES4 Descriptive Graph**

5.4.6 Improving University Performance OP

Table 5.53 and Figure 5.48 show the percentages and frequencies on enhancing organisational Performance (OP1), we can note that majority of the participants (n = 241) "strongly concurred" with the OP1 statement.

Table 5.53. OP1 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	8	3.0
	DA	8	3.0
	N	13	4.8
	AG	114	42.2
	SA	127	47.0
	Total	270	100.0

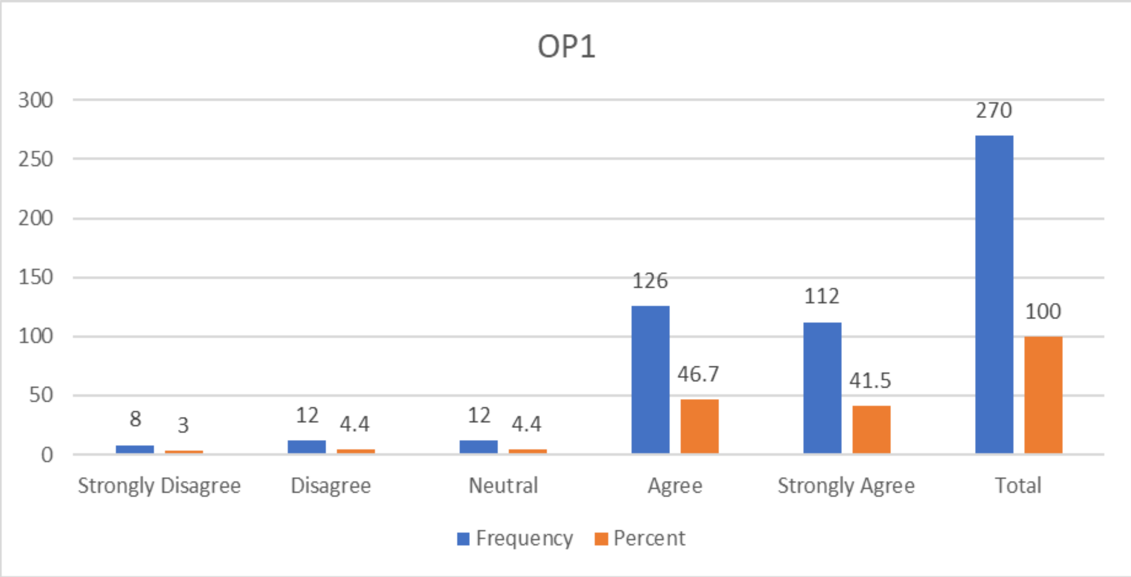

Figure 5.48. **OP1 Descriptive Graph**

Table 5.54 and Figure 5.49 show the percentages and frequencies on OP2, we can note that majority of the participants (n = 213) agreed with OP2 statement.

Table 5.54. OP2 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	8	3.0
	DA	17	6.3
	N	32	11.9
	AG	114	42.2
	SA	99	36.7
	Total	270	100.0

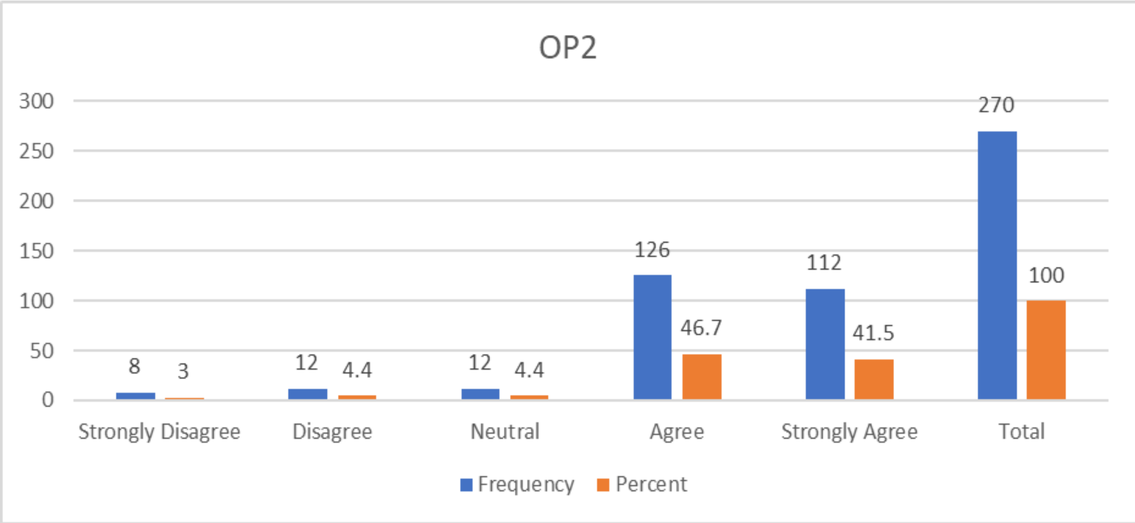

***Figure 5.49.* OP2 Descriptive Graph**

Table 5.55 and Figure 5. 50 show the percentages and frequencies of OP3; we can note that most participants (n = 223) "strongly concurred" with the OP3 statement.

Table 5.55. OP3 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	6	2.2
	DA	8	3.0
	N	23	8.5
	AG	134	49.6
	SA	99	36.7
	Total	270	100.0

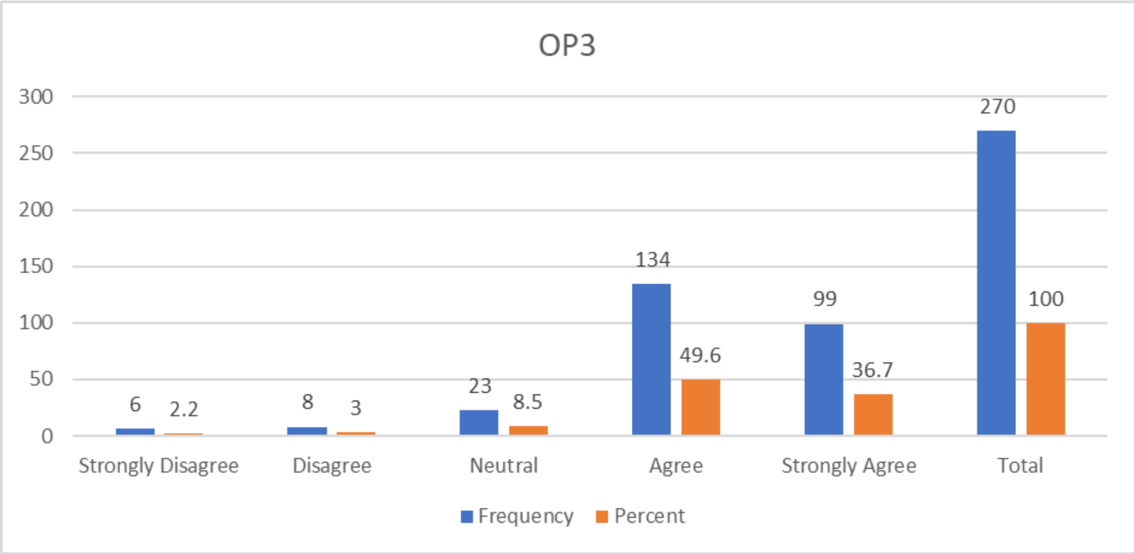

Figure 5.50. **OP3 Descriptive Graph**

Table 5.56 and Figure 5.51 show the percentages and frequencies on OP4; we can note that majority of the participants (n = 230) "strongly concurred" with OP4 statement.

Table 5.56. OP4 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	5	1.9
	DA	12	4.4
	N	23	8.5
	AG	127	47.0
	SA	103	38.1
	Total	270	100.0

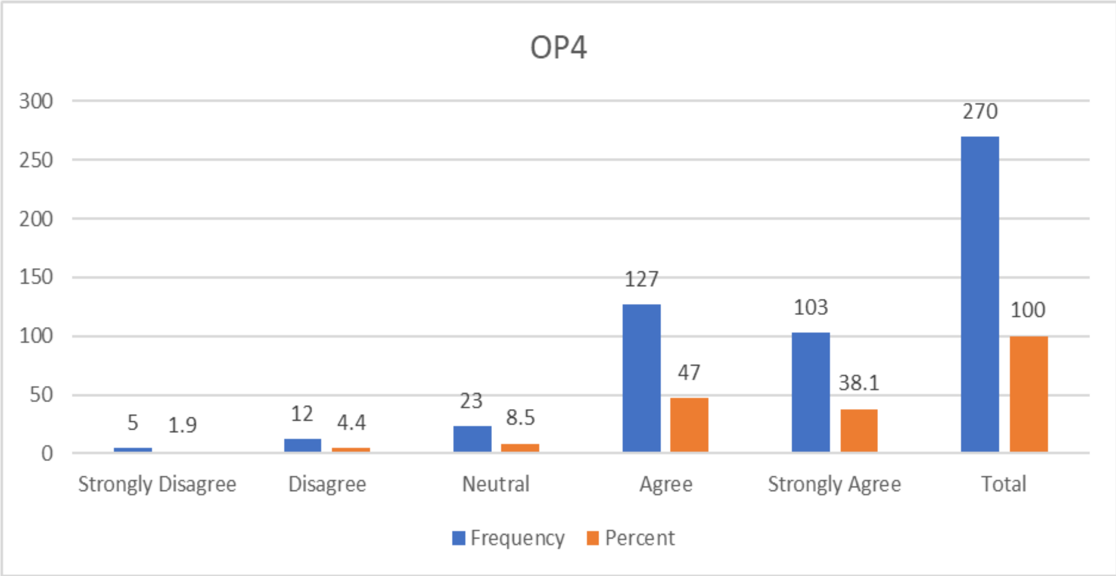

Figure 5.51. **OP4 Descriptive Graph**

Table 5.57 and Figure 5.52 show the percentages and frequencies on OP5; we can note that majority of the participants (n = 228) "strongly concurred" with the OP5 statement.

Table 5.57. OP5 – Descriptive Analysis

Statement		Frequency	Percent
Valid	SD	8	3.0
	DA	12	4.4
	N	12	4.4
	AG	126	46.7
	SA	112	41.5
	Total	270	100.0

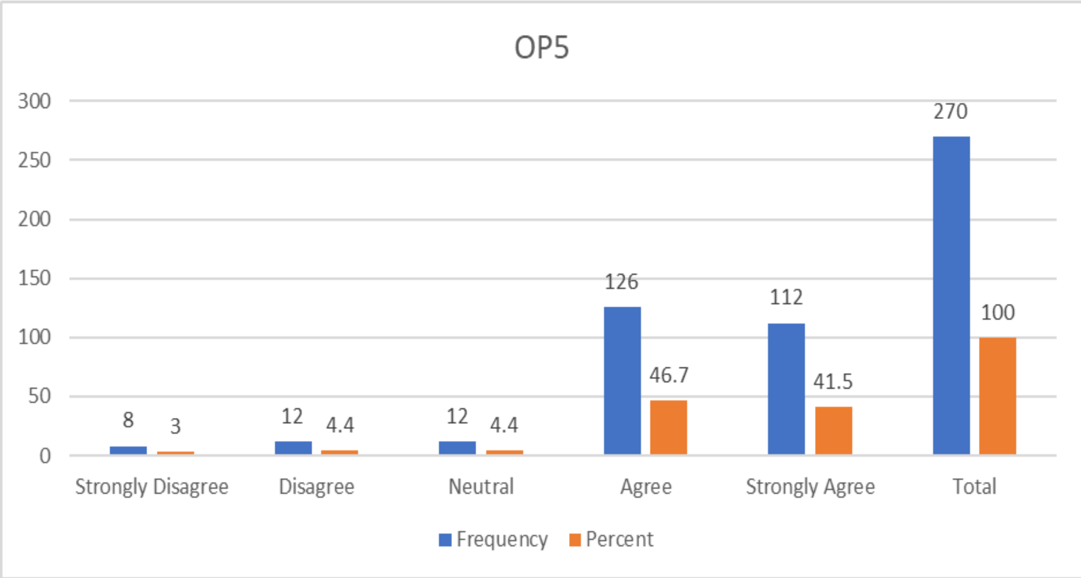

Figure 5.52. **OP5 Descriptive Graph**

5.5. Assessment of Mean, Standard Errors of Mean and Standard Deviation

The mean value gives the idea of the central tendency of the responses, while Standard Deviation (SD) expresses the variability or dispersion within the study sample, whereas Standard Error of Mean (SE) measures the uncertainty in the Mean estimates (Field, 2009). Variability in the data is also expressed in terms of Variance, which is the squared value of the SD or how the values differ from the mean value. We utilised SPSS v. 26 to calculate the Mean as a measure of central tendency (location), along with the SE and Variance for the study questionnaires, which were anchored on a Likert scale wherein 5 = Strongly-Agree; 4=Agree; 3=Neutral; 2=Disagree; and 1=Strongly-Disagree, to gather the responses from the study population. Each study questionnaire was incorporated collectively and at the items level to obtain the above inferences.

5.5.1. Means, SD, and SE for Big Data Performers

M, SD, SE and Variance for Big Data Performers, including IT Staff and Data Scientists, are shown in Table 5.58. BDP as a higher-order construct had a mean score above 4, which indicated that participants mostly agreed with the role of BDP in their organisations. Similarly, IT staff – measured through six items, and Data Scientists –

measured through three items – as lower order constructs of BDP also had mean scores above four hence endorsing the BDP mean value.

Table 5.58. BDP – Descriptive Analysis

Variables	N	Mean		Std. Deviation	Variance
	Statistic	Statistic	Std. Error	Statistic	Statistic
BDP	270	4.2348	.03329	.54704	.299
IT Staff	270	4.2655	.03468	.56988	.325
ITS1	270	4.4741	.04154	.68255	.466
ITS2	270	4.1593	.04233	.69558	.484
ITS3	270	4.2333	.04426	.72732	.529
ITS4	270	4.1963	.04523	.74324	.552
ITS5	270	4.2111	.04343	.71356	.509
ITS6	270	4.2593	.04293	.70540	.498
Data Scientists	270	4.1988	.04186	.68777	.473
DAS1	270	4.1963	.04731	.77746	.604
DAS2	270	4.2111	.04649	.76388	.584
DAS3	270	4.1852	.04464	.73353	.538
Valid N (listwise)	270				

5.5.2. Means, SD, and SE for OC

M, SD, SE and Variance for OC, including Accepting and Adapting, are shown in Table 5.59. OC as a higher-order construct had a mean score above 4, which indicated that participants mostly agreed with the role of OC in implementing big data-related changes in their organisations. Similarly, Accepting – measured through three items, and Adapting – also measured through three items – as lower order constructs of OC also had mean scores close or above 4, hence endorsing the BDP mean value.

Table 5.59. OC – Descriptive Analysis

Variables	N	Mean		Std. Deviation	Variance
	Statistic	Statistic	Std. Error	Statistic	Statistic
OC	270	4.0617	.04217	.69292	.480
Accepting	270	4.1395	.04507	.74055	.548

ACC1	270	4.2444	.05426	.89165	.795
ACC2	270	4.1148	.05421	.89076	.793
ACC3	270	4.0593	.05809	.95445	.911
Adapting	270	3.9840	.05133	.84346	.711
ADA1	270	3.9741	.06284	1.03259	1.066
ADA2	270	4.0037	.06286	1.03291	1.067
ADA3	270	3.9741	.06015	.98844	.977
Valid N (listwise)	270				

5.5.3. Means, SD, and SE for BDS

M, SD, SE and Variance for BDS, including Security, Privacy and Quality, are shown in Table 5.60. BDS as a higher-order construct had a mean score above 4, which indicated that participants mostly concurred with the role of BDS in big data dynamics in their organisations. Similarly, security – was measured through three items, Privacy – was measured through three items, and quality – was also measured through three items, as the lower order constructs of BDS also had mean scores close to or above 4, hence endorsing the BDP mean value.

Table 5.60. BDS – Descriptive Analysis

Variables	N	Mean		Std. Deviation	Variance
	Statistic	Statistic	Std. Error	Statistic	Statistic
BDS	270	4.2429	.03323	.54598	.298
Security	270	4.3746	.03351	.55063	.303
SEC1	270	4.6000	.03906	.64179	.412
SEC2	270	4.2926	.03994	.65635	.431
SEC3	270	4.2333	.03790	.62268	.388
Privacy	270	4.1136	.04965	.81575	.665
PRI1	270	4.1074	.05626	.92444	.855
PRI2	270	4.0333	.05899	.96923	.939
PRI3	270	4.2000	.05392	.88608	.785
Quality	270	4.2396	.03814	.62669	.393
QUA1	270	4.2407	.04474	.73508	.540

QUA2	270	4.2778	.04201	.69026	.476
QUA3	270	4.2000	.04185	.68765	.473
Valid N (listwise)	270				

5.5.4. Means, SD, and SE for BDT

M, SD, SE and Variance for BDT, including Storing, Analysing and Visualising, are shown in Table 5.61. BDT as a higher-order construct had a mean score of approximately 4, which indicated that participants almost concurred with the role of BDT in big data dynamics in their organisations. Similarly, storing – was measured through three items, Analysing – was measured through three items, and Visualising – was also measured through three items, as the lower order constructs of BDT also had mean scores close to or above 4, hence endorsing the BDT mean.

Table 5.61. BDT – Descriptive Analysis

Variables	N	Mean		Std. Deviation	Variance
	Statistic	Statistic	Std. Error	Statistic	Statistic
BDT	270	3.9216	.03935	.64655	.418
Storing	270	3.7667	.05742	.94356	.890
STO1	270	3.8222	.06611	1.08636	1.180
STO2	270	3.7407	.06404	1.05226	1.107
STO3	270	3.7370	.06056	.99502	.990
Analysing	270	3.9766	.04861	.79873	.638
ANA1	270	3.9778	.05324	.87482	.765
ANA2	270	3.9778	.05552	.91226	.832
ANA3	270	3.9741	.05152	.84664	.717
Visualising	270	4.0211	.04420	.72629	.528
VIS1	270	4.0630	.04922	.80871	.654
VIS2	270	3.9852	.04894	.80413	.647
VIS3	270	4.0148	.04780	.78542	.617
Valid N (listwise)	270				

5.5.5. Means, SD, and SE for Improving Decision Making

M, SD, SE and Variance for DES are shown in Table 5.62. DES as a single / higher order construct was measured through four items with a mean score of more than 4, indicating that respondents mostly concurred with the role of DM in implementing big data-related changes and systems in their organisations.

Table 5.62. DES– Descriptive Analysis

Variables	N	Mean		Std. Deviation	Variance
	Statistic	Statistic	Std. Error	Statistic	Statistic
Decision Making	270	4.3435	.03435	.56444	.319
DES1	270	4.5963	.04214	.69249	.480
DES2	270	4.2333	.04669	.76712	.588
DES3	270	4.2074	.04728	.77696	.604
DES4	270	4.3481	.04347	.71436	.510
Valid N (listwise)	270				

5.5.6. Means, SD, and SE for OP

M, SD, SE and Variance for OP are shown in Table 5.63. OP as a single / higher order construct was measured through five items with a mean score of more than 4, which indicated that participants mostly agreed that organisational performance improved with the proper role/implementation of OC, BDP, BDS, BDT and DES in their organisations.

Table 5.63 *OP* – Descriptive Analysis

Variables	N	Mean		Std. Deviation	Variance
	Statistic	Statistic	Std. Error	Statistic	Statistic
Performance	270	4.1615	.04148	.68157	.465
OP1	270	4.2741	.05550	.91196	.832
OP2	270	4.0333	.06105	1.00315	1.006
OP3	270	4.1556	.05267	.86542	.749
OP4	270	4.1519	.05413	.88937	.791
OP5	270	4.1926	.05676	.93265	.870
Valid N (listwise)	270				

5.6. Chapter Summary

The current chapter provided a very detailed descriptive analysis of the study participant through demographic information such as frequencies and percentages. We utilised pie charts and bar graphs to represent the same analysis for visual assessment. This chapter also covered the analysis of the study scales employing frequencies and percentages on each item of every questionnaire used in this study. We utilise histograms to visualise the responses from the study participants graphically. At the end of this chapter, we ran a descriptive analysis on the study questionnaires to determine the central tendencies and variability of the responses within the study population, and we utilised SPSS v. 26 to calculate the means, standard deviations, standard errors of the means and Variance or the squared coefficients of the standard deviation to estimate the actual variability of the data from the mean scores. The next chapter will cover the data analysis with respect to the measurement and structural models assessment to obtain more solid inferences on the data by utilising structural equation modelling (SEM) with the help of SmartPLS software.

CHAPTER 6

MEASUREMENT AND STRUCTURAL MODELS DATA ANALYSIS

6.1. Introduction

This chapter provides the details on data analysis, particularly on prerequisites such as collinearity among the scale items and hypotheses testing, which include the impact of (1) big data performers on big data systems and decision-making (2) the influence of organisational culture on big data tasks, system quality and decision making; (3) big data system quality and tasks on decision making; and (4) big data-enabled decision making on organisational performance. Online survey was utilised for collecting the data, which was later used to test the hypotheses by utilising PLS-SEM. The current chapter is organised in the following sequence. First, this study provides a collinearity diagnostic on the study variables at items level, by the means of variance inflation factor to detect multicollinearity. Then, this study provides the results on PLS structural model, statistical analysis on the data to examine the reliability and validity of the research's factors as well as testing the proposed hypothesis. And at the end of measurement model, we also conducted the PLS Predict robustness check, while at the end of the structural model we conducted the robustness checks such as quadratic effects and unobserved heterogeneity.

6.2. Collinearity Diagnostics

This chapter described the latent variables used in the PLS structural model based on their means, standard deviation, and variance inflation factors. Five- point Likert rating scale was applied to assess the proposed variables. The arithmetic mean value indicates the average of responses about each question, while the standard deviation depicts the dispersion of values about the mean (Martinez & Bartholomew, 2017). Multicollinearity poses potential problems to parameter estimates and their statistical significance, affecting our judgment of predictor variables (Thompson et al., 2017). Multicollinearity becomes a problem where predictor variables in a model are highly related (Thompson et al., 2017). Thus, we derived VIF values to rule out multicollinearity problems. The cut-off points for VIF values have been debated, but (Thompson et al., 2017) argue that one should consider VIF < 3 if the correlation coefficient ≤ 0.5, VIF < 5 if the correlation coefficient ≤ 0.67, VIF < 7 if the correlation coefficient ≤ 0.86, and VIF < 10 if correlation coefficient ≤ 0.90. Since our study's best correlation is .644, VIF < 5 adequately assesses multicollinearity.

Table 6.1. Collinearity Diagnostics for Big Data Performers

IT Staff		**Mean**	**SD**	**VIF**
ITS1	IT staff should be encouraged to secure big data	4.47	0.68	1.92
ITS2	In my university, the IT Staff rely on the system quality to ensure that big data is secured	4.16	0.70	2.20
ITS3	In my university, the IT staff should be responsible for the security of big data	4.23	0.73	2.10
ITS4	In my university, IT Staff rely on system to ensure that big data is private	4.20	0.74	2.29
ITS5	In my university, the IT staff should be responsible for the privacy of big data	4.21	0.71	2.26
ITS6	IT staff should have a policy standard for big data privacy	4.26	0.71	2.02
DAS1	In my university, Data Scientists are important for evaluating big data quality	4.20	0.78	2.79

DAS2	In my university, Data Scientists are crucial for maintaining big data quality	4.21	0.76	2.64
DAS3	In my university, Data Scientists are a vital human factor in storing, analysing, and visualising analysed big data	4.19	0.73	3.64

According to the mean values recorded in Table 6.1, respondents mainly indicated that staff should be encouraged to secure big data ($\bar{x}$ = 4.47). Also, participants agreed to IT staff being responsible for big data security ($\bar{x}$ = 4.16) and creating a standard policy on big data privacy ($\bar{x}$ = 4.23). Furthermore, participants concurred that IT staff rely on the quality of systems to ensure big data security ($\bar{x}$ = 4.20), keep data private ($\bar{x}$ = 4.21), and take responsibility for big data privacy ($\bar{x}$ = 4.26). Participants were also asked about data scientists as another category of big data performers that play a critical role in ensuring that the quality of big data is taking place for improving the decision-making. They agreed that data scientists are crucial in ensuring big data quality ($\bar{x}$ = 4.20) and are an important factor in storing, analysing, and visualising big data ($\bar{x}$ = 4.21). Participants agreed that data scientists are crucial in evaluating big data quality ($\bar{x}$ = 4.19).

Table 6.2. Collinearity diagnostics for Big Data System

Items: Big Data Security		Mean	SD	VIF
SEC1	Data protection in big data systems is very important for maintaining data security	4.60	0.64	1.67
SEC2	Restricting data access in big data systems is very important for maintaining data security	4.29	0.66	2.53
SEC3	Analysed data that is used for decision-making should be accessed only by decision-makers	4.23	0.62	2.36
Items: Big Data Privacy				
PRI1	Big data systems should have controls for data sharing	4.11	0.92	2.02
PRI2	Big data systems should protect information about the personal identity of decision-makers	4.03	0.97	2.60
PRI3	The university should have a policy standard for big data privacy	4.20	0.89	2.46
Items: Big Data Quality				
QUA1	The quality of big data is crucial	4.24	0.74	2.22
QUA2	Technological improvements should include Implementing big data system for big data quality	4.28	0.69	3.19
QUA3	The quality of big data is vital for decision making	4.20	0.69	2.58

In Table 6.2, we summarise how participants responded to indicators of big data system quality. System quality was measured based on big data security, privacy, and quality. On big data security, participants agreed that data protection is a very important aspect of big data security ($\bar{x}$ = 4.60), restricting data access in big data systems is very important for maintaining data security ($\bar{x}$ = 4.29), and that analysed data should be accessed only by decision-makers ($\bar{x}$ = 4.23).

On big data privacy, participants agreed mainly to institutions creating a standard policy on big data privacy ($\bar{x}$ = 4.11). They also agreed big data systems should have controls for data sharing ($\bar{x}$ = 4.03), and those big data systems should protect information about the personal identity of decision-makers ($\bar{x}$ = 4.20).

Regarding big data quality, participants mainly agreed that big data quality is crucial ($\bar{x}$ = 4.24) and that technological improvement for big data systems should focus on big data quality ($\bar{x}$ = 4.28). They also agreed that big data quality is crucial for decision-making ($\bar{x}$ = 4.20).

Table 6.3. Collinearity Diagnostics for Big Data Tasks

Items: Storing		**Mean**	**SD**	**VIF**
STO1	My university has the ability to store very large, unstructured, or fast-moving data	3.82	1.09	2.25
STO2	My university has the capability of storing big data from various reliable sources	3.74	1.05	3.39
STO3	My university has the ability to store multiple big data from (internal and external) sources	3.74	1.00	3.03
Items: Analysing				
ANA1	My university has the ability to analyse big data	3.98	0.87	2.77

ANA2	My university has the ability to analyse big data from internal and external resources	3.98	0.91	3.38
ANA3	My university has the capability to analyse big data from various reliable resources	3.97	0.85	3.01
Items: Visualising				
VIS1	My university has the ability to visualise analysed big data.	4.06	0.81	2.80
VIS2	My university has the ability to visualise analysed big data from internal and external resources.	3.99	0.80	3.36
VIS3	My university has the capability to visualise analysed data from various reliable resources.	4.01	0.79	2.85

Table 6.3 summarises the indicators measuring big data tasks, emphasising storing, analysing, and visualising tasks. Participants reacted almost neutrally to storing very large unstructured fast-moving data ($\bar{x}$ = 3.82), storing internal and external derived data ($\bar{x}$ = 3.74), and storing data from various sources ($\bar{x}$ = 3.74). Participants seemed to agree to analysing and visualising big data. They indicated that institutions could analyse big data ($\bar{x}$ = 3.98), do so from internal and external sources ($\bar{x}$ = 3.98), as well as analysing data from reliable sources ($\bar{x}$ = 3.97). Regarding big data visualising, participants agree that their institutions can visualise big data ($\bar{x}$ = 4.06), both from internal and external ($\bar{x}$ = 3.99), and reliable sources ($\bar{x}$ = 4.01).

Table 6.4. Collinearity Diagnostics for Organisational Culture.

Items: Organisational Culture		Mean	SD	VIF
ACC1	My university will accept new innovations such as big data analytics	4.24	0.89	1.43
ACC2	My university will accept big data technological improvements	4.11	0.89	1.69
ACC3	My university will accept technological upgrades for big data analytics	4.06	0.95	1.80
ADA1	My university always keens on new changes such as big data analytics technological improvements	3.97	1.03	1.61
ADA2	My university plans to adapt to new technological changes in big data analytics	4.00	1.03	1.83
ADA3	My university would adapt to new technological changes for big data analytics	3.97	0.99	1.82

Table 6.4 summarises the indicators of organisational culture concerning accepting and adapting technological improvements for big data. Participants mainly agreed that their institutions accept innovations in big data ($\bar{x} = 4.24$), big data technological improvements ($\bar{x} = 4.11$), and upgrades for big data analytics ($\bar{x} = 4.06$). Participants also agreed that their institutions are keen on big data changes ($\bar{x} = 3.97$); they plan to adopt these changes ($\bar{x} = 4.00$) and would most certainly adopt technological improvements for big data ($\bar{x} = 3.97$).

Table 6.5. Collinearity Diagnostics for Decision Making

Items: Decision Making		Mean	SD	VIF
DES1	Big data analytics system will improve the effectiveness of decision-making.	4.60	0.69	1.35
DES2	Big data analytics system will help top management to make their decision faster	4.23	0.77	1.73
DES3	Big data analytics system will increase the number of decisions made by top management	4.21	0.78	1.60
DES4	Big data analytics system will increase the confidence of top management to make decisions based on analysed data	4.35	0.71	1.48

As shown in Table 6.5, participants were also asked questions regarding big data-enabled decision-making. They indicated that big data systems enable effective decision-making ($\bar{x}$ = 4.60), faster decision-making ($\bar{x}$ = 4.23), build decision-making confidence ($\bar{x}$ = 4.21), and increase the number of decisions that top managers can make ($\bar{x}$ = 4.35).

Table 6.6. Collinearity Diagnostics for Organisational Performance

Items: Organisational Performance		Mean	SD	VIF
PER1	The numbers of decisions made by analysed data are increased for better performance.	4.27	0.91	1.54
PER2	Big data analytics saves the costs of hiring experts for making decisions	4.03	1.00	1.76

PER3	Big data analytics system will help top management to improve scientific research and development	4.16	0.87	1.96
PER4	Big data analytics will create business value	4.15	0.89	1.57
PER5	Big data analytics will improve the overall university's performance	4.19	0.93	1.52

Our study sought to investigate the impact of big data-enabled decision-making on organisational performance. Regarding the latter, respondents indicated that the number of decisions increases for better performance ($\bar{x} = 4.27$). They also agreed that big data analytics saves costs for hiring experts ($\bar{x} = 4.03$), improves research and development ($\bar{x} = 4.16$), creates business value ($\bar{x} = 4.15$), and overall performance of the institution ($\bar{x} = 4.19$).

After the descriptive analysis of constructs and their indicators, we delved into model estimation and hypothesis results. In the subsequent section, we have shown the inferential results on both measurement and structural models from PLS-SEM.

6.3. Model Estimation and Results

Like numerous research, our initial step was establishing a research goal, as discussed in Chapter 1. We then specified the model in Figure 3.10 in Chapter 3, which we tested using the PLS-SEM approach. The covariance-based (CB-SEM) and PLS-SEM are the subtypes of SEM. In estimating the model, the former applies an approach termed a common factor model, while the latter applies a composite model approach (Ringle et al., 2020). The common factor approach assumes "the variance numbers of indicators will be able to explain unobserved factor (or common factor). While the composite model technique operates on the assumption that the composites factors may be defined by combinations of indicators." (Ringle et al., 2020).

PLS-SEM is useful for studies with non-normal data, sample sizes, and categorical variables, but, most importantly, this study supports explorative analyses (Ringle et al., 2020; Hair et al., 2020). We based on (Hair et al., 2017) sample size recommendations. Therefore, we determined that since we had four independent variables hypothesised to affect decision-making, we needed a sample of 113 observations (but used 270) to accomplish a statistical power equal to 80% while considering R^2 equal to 0.10 at 5% significance level. However, some authors (e.g., Wong, 2019) questioned the ability of PLS-SEM to handle multicollinearity problems. Fortunately, our data indicated no collinearity problems, as indicated by the VIF values in Table 6.1 to Table 6.6.

6.4. Measurement Model

Measurement models specify latent variables, and two theories applied – reflective and formative measurements. Reflective types of items *reflect* the underlying construct(s) (MacKenzie et al., 2011) and thus indicate that "the study constructs cause the measurements (or the covariations) of the indicator variables" (Hair et al., 2017, p. 13). Formative types of indicators *form* the relevant constructs (MacKenzie et al., 2011) and thus indicate casual (predictive) relationships from the indicator items to the construct (Hair et al., 2017). Formative indicators are not interchangeable and may have a positive, negative, or no correlation, while reflective indicators are interchangeable, and highly correlated, and their validity is critical (Petter et al., 2007; Wong, 2019). Furthermore, reflective indicators are expected to covary, and their nomological net should not differ (Petter et al., 2007).

Aligned with Sarstedt, Hair, Cheah, Becker & Ringle (2019), a Type-I Reflective-Reflective lower and higher-order constructs model was deemed appropriate to be evaluated for the measurement. We used the repeated indicator approach to measure our model (Becker et al., 2012; Agarwal & Karahanna, 2000). It simultaneously measures lower and higher-order constructs (LOC & HOC), so it's easy to implement (Sarstedt et al., 2019). The following methods are involved in assessing and validating the reflective-reflective measurement model. The constructs, items, outer loadings, and measurement reliability and validity are summarised in the following parts of the document.

Factor Loadings: A construct is considered reliable if its items' factor loadings (FL) are equal or > .50 (Hair et al., 2019). Comrey & Lee (1992) provided guiding categories of FL quality i.e., excellent if FL > .71, very good if FL > .63, good if FL > .55, fair if FL >

.45, and poor if FL < 0.32. Most of the study scales' FL were > .53 (see Table 6.7 and Figure 6.1), which provided a base reliability of the study scales.

Table 6.7. Factor Loadings

BDP		**OC**		**BDS**		**BDT**		**DES**		**OP**	
Item	FL	Item	FL	Item	FL	Item	FL	Item	FL	Item	FL
ITS		ACC		PRI		STOR		DES		OP	
ITS1	0.77	ACC1	0.74	PRI1	0.85	STO1	0.88	DES1	0.67	OP1	0.68
ITS2	0.8	ACC2	0.84	PRI2	0.9	STO2	0.93	DES2	0.84	OP2	0.74
ITS3	0.8	ACC3	0.85	PRI3	0.89	STO3	0.91	DES3	0.79	OP3	0.84
ITS4	0.83	ADA		QUA		ANA		DES4	0.76	OP4	0.7
ITS5	0.82	ADA1	0.79	QUA1	0.87	ANA1	0.9			OP5	0.73
ITS6	0.79	ADA2	0.84	QUA2	0.92	ANA2	0.92				
DAS		ADA3	0.86	QUA3	0.88	ANA3	0.91				
DAS1	0.9			SEC		VIS					
DAS2	0.9			SEC1	0.79	VIS1	0.9				
DAS3	0.94			SEC2	0.9	VIS2	0.92				
				SEC3	0.88	VIS3	0.9				

Internal Consistency: To establish the reliability or the internal consistency of the measurement model, Cronbach's α for each of the measures is supposed to be > .7 (Hair et al., 2019), whose estimations for this study met the criteria very well (see Table 6.8 & Figure 6.1).

Considering the issues with underestimating with Cronbach's α, composite reliability is supposed to be checked to determine the true reliability to the optimum level (Garson, 2012). As shown in Table 6.8, this study's measurement model met the CR criteria, > 0.7 (Ringle, 2020).

Convergent Validity (CV): It can be defined as the agreeableness of the varied approaches in varied attempts to quantify exactly the same theory (Bagozzi, 1980). Besides, AVE (average variance extracted) is required to > 0.5 (Hair et al., 2020). As shown in Table 6.8 that AVE values for all scales were well above the required criteria to establish their convergent validity.

Table 6.8. Factor Loadings, Reliability, Validity and Quality of the Model

Variable	Cronbach's Alpha	Composite Reliability	AVE	H^2
Big Data Performers	0.895	0.915	0.544	0.436
IT Staff	0.888	0.915	0.642	0.494
Data Scientists	0.895	0.935	0.826	0.615
Organisational Culture	0.811	0.864	0.514	0.315
Accepting	0.740	0.853	0.659	0.32
Adapting	0.772	0.868	0.688	0.368
Big Data System	0.883	0.906	0.519	0.407
Privacy	0.854	0.912	0.775	0.523
Quality	0.869	0.920	0.792	0.553
Security	0.823	0.894	0.739	0.466
Big Data Tasks	0.882	0.906	0.52	0.400
Storing	0.887	0.930	0.816	0.596
Analysing	0.895	0.935	0.827	0.613

Visualisation	0.894	0.934	0.825	0.611
Making Decisions DES	0.764	0.850	0.587	0.317
Performance	0.794	0.859	0.550	0.327

Discriminant Validity DV: Studies have advanced multiple approaches for analysing the DV of the latent variables, including the Fornell-Larker criterion, cross-loadings, and HTMT ratios. Because the Fornell-Larker criteria and factors' cross-loadings are insufficient to detect discriminant validity problems between variables, a more robust alternative technique, Heterotrait-Monotrait ratios (HTMT), was applied in this study. HTMT embodies the average scores of the correlations among indicators across the study constructs in relation to the geometric averages of the correlations means of the indicators using the same measurement scale (Ringle et al., 2020). The usually accepted limit is $HTMT_{.85}$ or $HTMT_{.90}$ depending on the theory (Henseler et al., 2015; Kline, 2016), while HTMT value closer to 1 indicates a poor discriminant validity of the measures.

This study concluded the discriminant validity based on $HTMT_{.90}$, which is a more liberal threshold applied in most studies, including information systems research. Moreover, when constructs are conceptually distinct (not conceptually similar), Henseler et al., 2015 strongly suggested that HTMT levels not exceed 0.85. Since the HTMT values in Table 6.9 are all below 0.90, except for high order constructs (HOC), so this study concluded that discriminant validity was established between the measurement model variables, as shown in Figure 6.1. HOCs cannot be used to solve discriminant issues (Kocyigit & Ringle, 2011). Therefore, HOCs must show discriminant validity with all other lower-order constructs (LOCs) and HOCs in the model, except for their own LOCs. Similarly, all LOCs in the model must show discriminant validity with all other HOCs and LOCs except with their HOC (Sarstedt et al., 2019). So, we concluded that our constructs had sufficient discriminant validity. Additionally, through the bootstrapping procedure, we determined that all HTMT values were significantly < 1, as recommended by (Ringle et al., 2020).

Table 6.9. Discriminant Validity Using HTMT Ratio

	BDP	ITS	DAS	OC	ACC	ADA	BDS	PRV	QLT	SEC	BDT	STO	ANA	VIS	DES	OP
BDP																
ITS	1.049															
DAS	0.874	0.574														
OC	0.442	0.428	0.324													
ACC	0.483	0.453	0.377	1.125												
ADA	0.321	0.323	0.212	1.108	0.698											
BDS	0.397	0.44	0.192	0.289	0.321	0.204										
PRI	0.324	0.344	0.182	0.223	0.256	0.149	0.967									
QUA	0.376	0.425	0.167	0.287	0.295	0.226	0.94	0.532								
SEC	0.298	0.337	0.133	0.216	0.254	0.139	0.932	0.627	0.631							
BDT	0.34	0.322	0.26	0.287	0.208	0.309	0.261	0.193	0.182	0.281						
STO	0.321	0.321	0.217	0.215	0.137	0.25	0.244	0.297	0.15	0.165	0.795					
ANA	0.234	0.203	0.212	0.264	0.21	0.267	0.171	0.08	0.144	0.209	0.932	0.358				
VIS	0.247	0.237	0.184	0.197	0.143	0.212	0.199	0.08	0.137	0.288	0.947	0.395	0.718			
DES	0.355	0.323	0.297	0.268	0.32	0.169	0.529	0.482	0.485	0.353	0.474	0.443	0.337	0.339		
OP	0.381	0.38	0.26	0.45	0.429	0.386	0.399	0.374	0.308	0.318	0.342	0.378	0.218	0.213	0.55	

Measurement Model Quality Assessment: The features of eminence quality are translated by the predictive validity model's measurement. The predictive relevance of model's measurement can be assessed with the help of commonality (H^2) values using PLS blindfolding option. All values of the predictive relevance for the study model were positive for all model portions or blocks (Table 6.8), thus, the predictive quality/validity of the model's measurement was duly established.

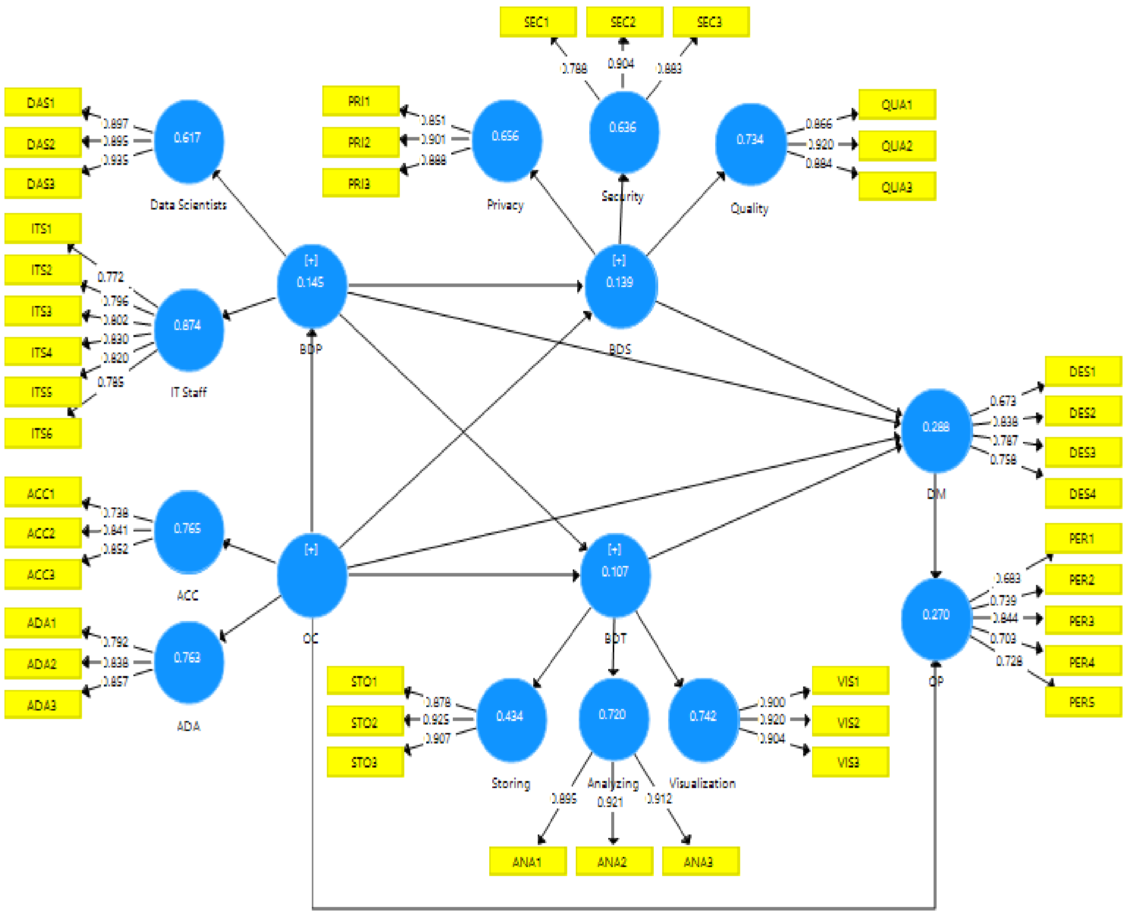

Figure 6.1. **Measurement Model**

6.4.1. Measurement Model Robustness

The measurement model's robustness check can be done using PLS Predict primarily (Sarstedt et al., 2019).

PLS-Predict: This analysis is used for assessing the analytical capability of the model. PLS-Predict is a robustness procedure based on the sample, and it produces predictions on the case level at the construct and item level. Divergent from the traditional structural model assessment techniques such as the R^2 and Q^2, PLS-Predict provides methods to assess a structural model's capacity to predict a number of variables; such power can be termed as the model's accuracy in predicting the outcome values of the new cases. We utilised the PLS-Predict utility (r = 10, k =10) in SmartPLS to check the measurement model's robustness following Hair, & Ringle (2019).

The first step in PLS Predict is to look at the prediction errors to assess their distribution pattern. As shown in Figure 6.2 to Figure 6.6. Those errors were apparently symmetrically distributed, so the root mean squared error data was considered to be used for making decisions, but we also used mean absolute error (MAE) statistics as well to rule out ambiguities, if any. The root-mean-square error (RMSE) is defined as the average squared deviation from the expectations & the actual observations.

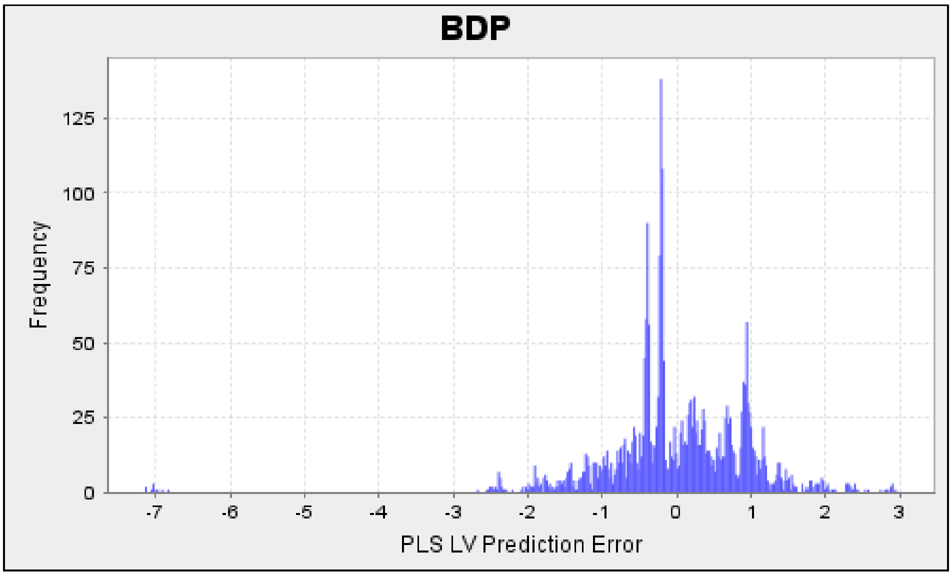

Figure 6.2. BDP Prediction Errors Distribution

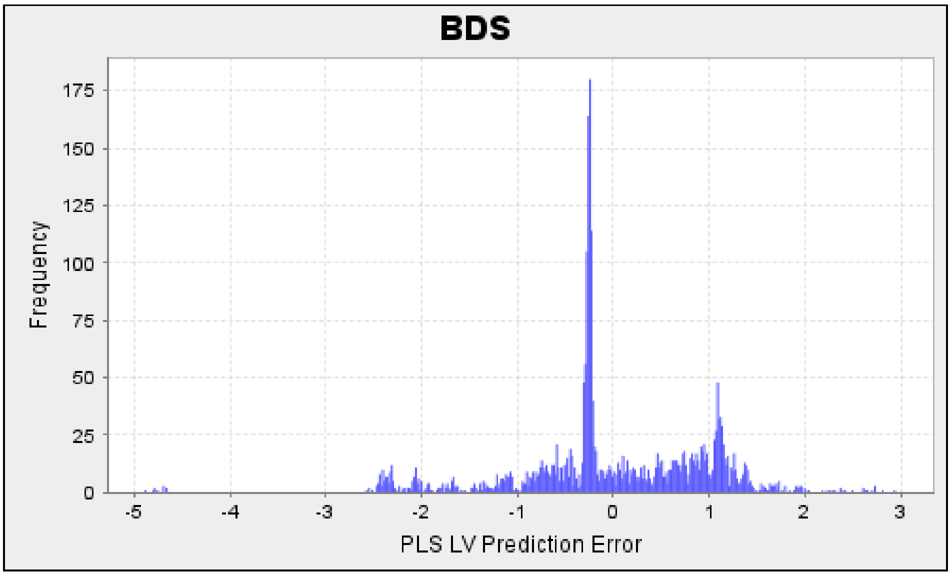

Figure 6.3. **BDS Prediction Errors Distribution**

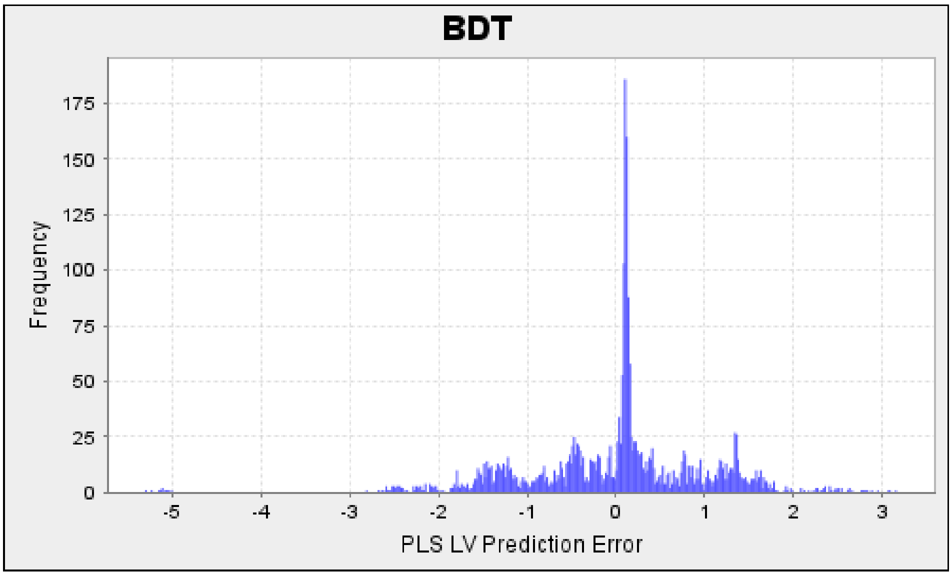

Figure 6.4. BDT Prediction Errors Distribution

The MAE technique evaluates the mean size of the errors in a collection of projections devoid of contemplating their focus (on or underneath); MAE is the mean principle differences between predicted results and observed data, along with all the particular differences of the same weight.

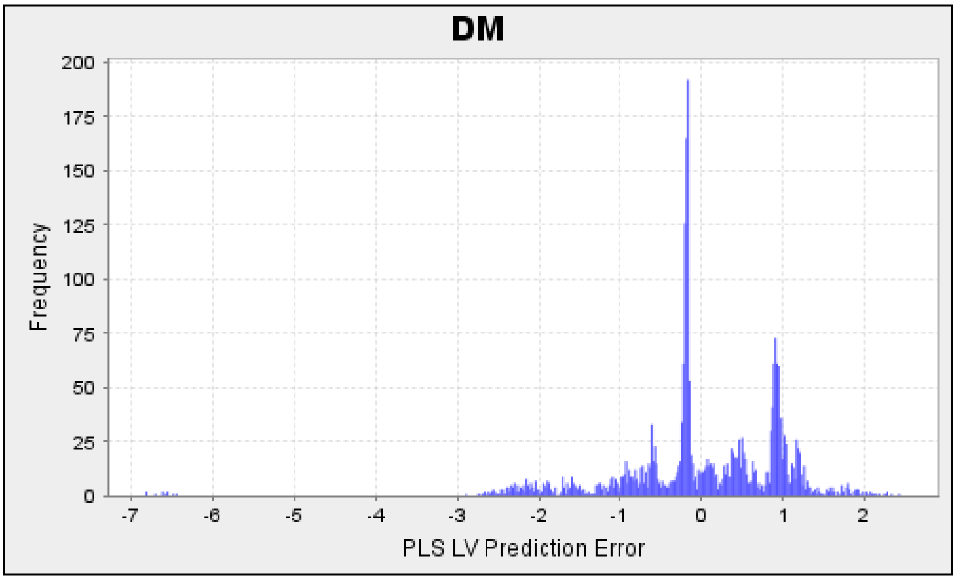

Figure 6.5. **DES Prediction Errors Distribution**

Next, as noted in Table 6.10, all the indicators of the endogenous variables, i.e., BDP, BDT, BDS, DES and OP, overtook the naïve benchmarks as Q^2 was > 0 for both PLS-SEM and linear regression model (LM) benchmarks. Then, we compared the RMSE and MAE performance measures and found that most of the PLS values were lower than those RMSE and MAE, which indicated the medium prognostic significance (Shmueli et al., 2019).

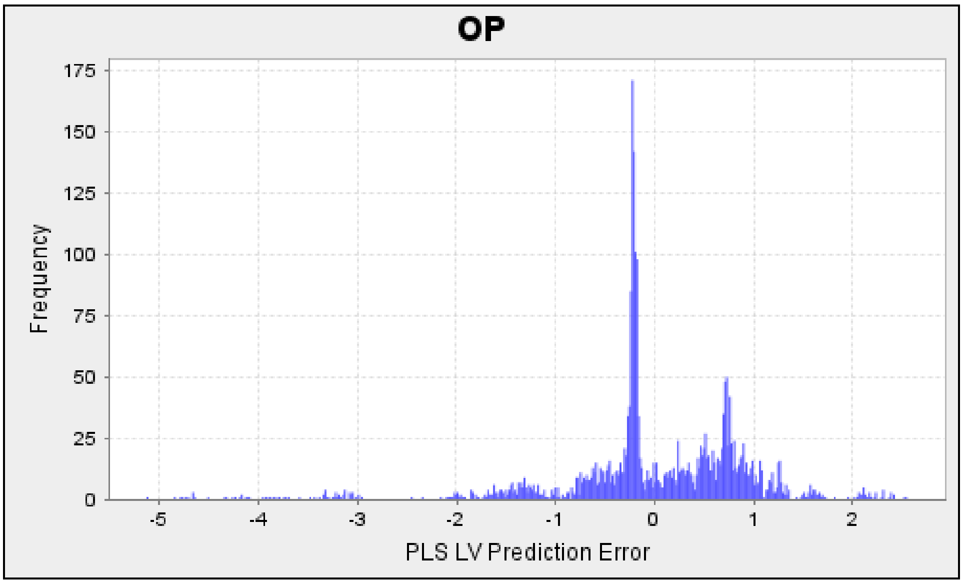

Figure 6.6. **OP Prediction Errors Distribution**

Table 6.10. PLS Predict – Indicators Comparison

PLS				LM				PLS - LM	
	RMSE	MAE	Q²	RMSE	MAE	Q²	RMSE	MAE	Q²
ANA1	0.868	0.601	0.021	0.879	0.631	-0.005	-0.011	-0.030	0.026
ANA2	0.890	0.652	0.052	0.901	0.674	0.029	-0.011	-0.022	0.023
ANA3	0.841	0.596	0.018	0.854	0.625	-0.014	-0.013	-0.029	0.032
DAS1	0.764	0.569	0.039	0.771	0.576	0.019	-0.007	-0.007	0.020
DAS2	0.744	0.572	0.055	0.740	0.570	0.066	0.004	0.002	-0.011
DAS3	0.708	0.533	0.071	0.724	0.549	0.031	-0.016	-0.016	0.040

DES1	0.689	0.545	0.013	0.672	0.503	0.061	0.017	0.042	-0.048
DES2	0.756	0.576	0.034	0.755	0.579	0.037	0.001	-0.003	-0.003
DES3	0.772	0.605	0.016	0.763	0.600	0.040	0.009	0.005	-0.024
DES4	0.717	0.587	-0.001	0.710	0.572	0.017	0.007	0.015	-0.018
ITS1	0.654	0.550	0.084	0.664	0.551	0.056	-0.010	-0.001	0.028
ITS2	0.655	0.477	0.117	0.663	0.489	0.096	-0.008	-0.012	0.021
ITS3	0.705	0.560	0.066	0.713	0.573	0.043	-0.008	-0.013	0.023
ITS4	0.719	0.567	0.068	0.726	0.566	0.051	-0.007	0.001	0.017
ITS5	0.687	0.543	0.076	0.698	0.557	0.045	-0.011	-0.014	0.031
ITS6	0.685	0.553	0.060	0.697	0.568	0.029	-0.012	-0.015	0.031
PER1	0.893	0.648	0.045	0.896	0.636	0.038	-0.003	0.012	0.007
PER2	0.968	0.688	0.072	0.982	0.709	0.046	-0.014	-0.021	0.026
PER3	0.830	0.580	0.086	0.827	0.601	0.092	0.003	-0.021	-0.006
PER4	0.874	0.619	0.042	0.874	0.625	0.040	0.000	-0.006	0.002
PER5	0.900	0.632	0.074	0.919	0.654	0.035	-0.019	-0.022	0.039
PRI1	0.928	0.653	-0.005	0.946	0.673	-0.044	-0.018	-0.020	0.039
PRI2	0.949	0.664	0.044	0.935	0.691	0.072	0.014	-0.027	-0.028
PRI3	0.878	0.653	0.023	0.881	0.657	0.017	-0.003	-0.004	0.006
QUA1	0.725	0.575	0.031	0.731	0.577	0.014	-0.006	-0.002	0.017
QUA2	0.688	0.559	0.010	0.675	0.545	0.047	0.013	0.014	-0.037
QUA3	0.685	0.522	0.010	0.676	0.523	0.036	0.009	-0.001	-0.026
SEC1	0.633	0.528	0.032	0.624	0.497	0.058	0.009	0.031	-0.026
SEC2	0.649	0.535	0.026	0.646	0.534	0.037	0.003	0.001	-0.011
SEC3	0.612	0.485	0.040	0.613	0.487	0.035	-0.001	-0.002	0.005
STO1	1.082	0.803	0.010	1.103	0.813	-0.030	-0.021	-0.010	0.040

STO1	1.082	0.803	0.010	1.103	0.813	-0.030	-0.021	-0.010	0.040
STO2	1.041	0.811	0.024	1.053	0.788	0.001	-0.012	0.023	0.023
STO3	0.986	0.765	0.022	0.997	0.759	0.001	-0.011	0.006	0.021
VIS1	0.810	0.596	0.001	0.817	0.608	-0.016	-0.007	-0.012	0.017
VIS2	0.799	0.563	0.016	0.817	0.580	-0.029	-0.018	-0.017	0.045
VIS3	0.782	0.540	0.015	0.798	0.567	-0.026	-0.016	-0.027	0.041
BDP			0.126						
BDS			0.044						
BDT			0.039						
DES			0.026						
OP			0.113						

6.5. Assessment of Structural Model

Upon satisfying the requirements of validity and reliability related to the measurement model, this study examined the structural paths model and hypothesis findings. A structural path model demonstrates the connection between constructs derived from theory and supported in literature or based on the researcher's experiences (Hair et al., 2017). The socio-technical theories drive the structures of relations specified in the model, see Figure 6.7, to describe the effect of big data performers and organisational culture on big data tasks and big data systems' quality towards strategic decision-making and organisational performance**.** We considered the relevance and Path coefficients' significance, determination coefficient (R^2), effect size (f^2), and predictive significance (Q^2) to assess our structural model. We applied 95% confidence intervals in bootstrapping to assess the significance of path estimates. Hair et al. (2017) specified that "It is recommended that at least 5,000 bootstrap samples be taken, while this number should ideally be higher than the number of actual observations." (p. 208). Therefore, we used 5,000 bootstrap samples in this study. Learning from Cohen (1998), f^2 equal to 0.02 falls within the category of being diminutive, 0.15 as an average and 0.35 as a big effect of the exogenous construct on an endogenous construct" (Hair et al., 2017, p. 208).

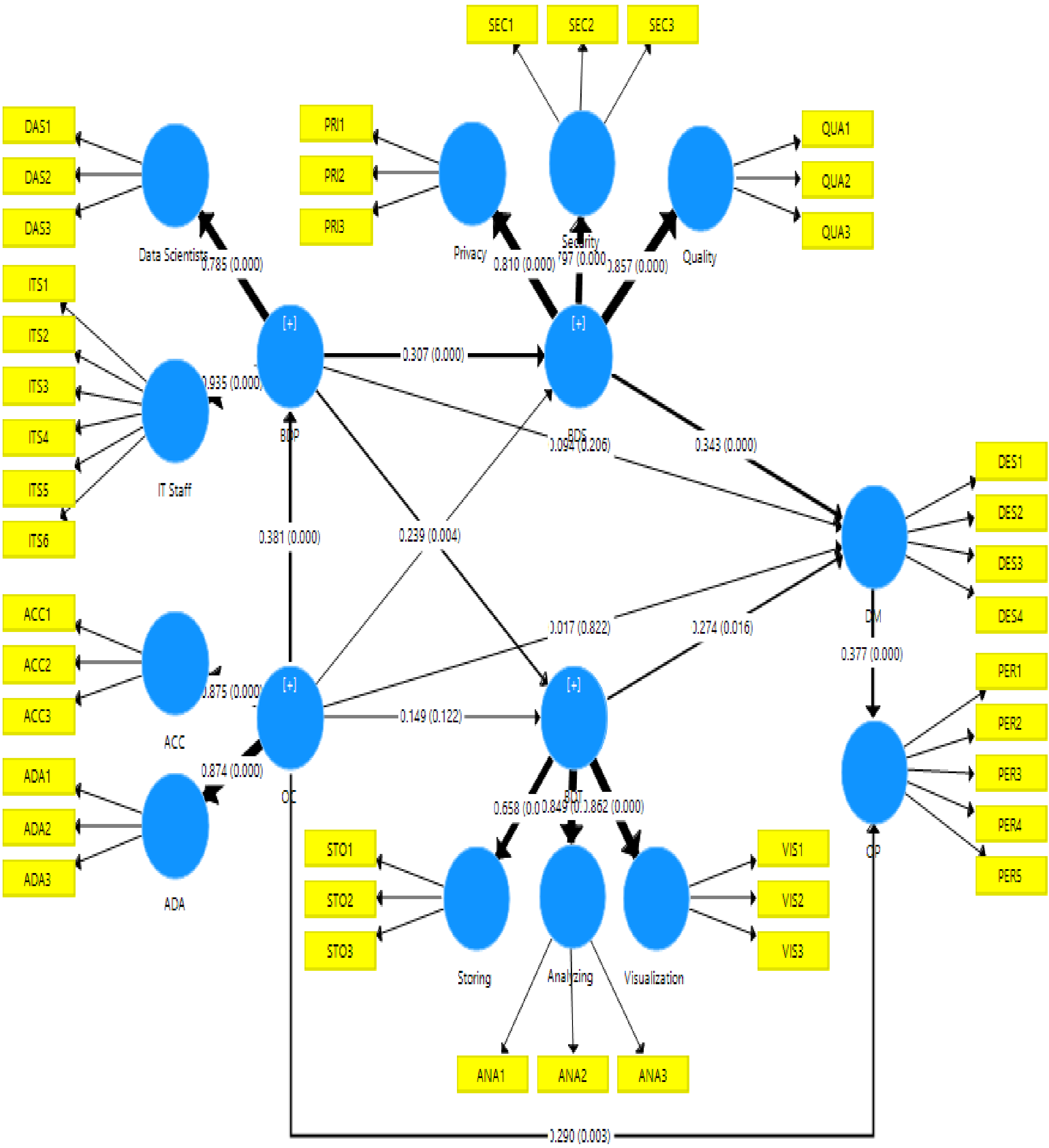

Figure 6.7. **Structural Model**

The model above indicates six HOCs, including OC with two LOCs i.e., accepting and adapting; big data performers with two LOCs i.e., IT staff and data scientists; BDS with three LOCs i.e., quality, security and privacy; BDT with three LOCs i.e., storing, analysing and visualising; decision making; and organisational performance. When testing our hypothesised relationships, we assumed a 5% significance level and resolved that an effect would be considered as significant if $p < 0.05$. Consequently, it was also resolved that the generally employed significant level for the two-tailed *t* value would be 1.96. Based on these resolutions, the hypotheses results are summarised in Table 6.11.

6.5.1. Hypothesis Results

All of our variables were associated with each other in a direct link, meaning that we did not propose any mediation or moderation models. Therefore, hypothesis testing was carried out as a direct effect analysis. It's also known as bivariate analysis since we deployed SEM using the PLS technique, therefor PLS algorithm for effect size and bootstrapping for importance of path coefficients has been applied. The outcomes of the hypotheses are presented in Table 6.11, along with the final status of the hypotheses. The interpretation for each hypothesis follows the details of the results.

Table 6.11. Hypothesis Results

Path	Estimate	SE	T Value	P Value	F^2	Status
BDP → BDS	0.307	0.084	3.643	0.000	0.094	H1: Supported
BDP → BDT	0.239	0.083	2.868	0.004	0.055	H2: Supported
OC → BDS	0.124	0.093	1.326	0.185	0.015	H3: Not Supported
OC → BDP	0.381	0.081	4.705	0.000	0.170	H4: Supported
OC → BDT	0.149	0.096	1.548	0.122	0.021	H5: Not Supported
OC → DES	0.017	0.078	0.225	0.822	0.000	H6: Not Supported
OC → OP	0.29	0.097	2.991	0.003	0.110	H7: Supported

BDS → DES	0.343	0.071	4.811	0.000	0.141	H8: Supported
BDT → DES	0.274	0.113	2.425	0.016	0.092	H9: Supported
DES → OP	0.377	0.098	3.852	0.000	0.186	H10: Supported
BDP → DES	0.094	0.074	1.266	0.206	0.010	H11: Not Supported

Hypothesis 1 postulated that BDP, including IT staff and data scientists, would positively affect BDS in terms of security, privacy, and quality. Our findings demonstrate that BDP had a significant effect on BDS ($\beta = .307$, $t = 3.643$, $p < .001$) with a small effect size ($F^2 = .094$), so H1 was supported, see Table 6.11.

In hypothesis 2, BDP was also supposed to positively impact BDT, including storing, analysing and visualisation. However, although, as shown in Table 6.11, BDP had a significant positive effect on BDT ($\beta = .239$, $t = 2.868$, $p = .004$), the effect size of BDP on BDT was small as well ($F^2 = .055$), this result confirmed that H2 was also supported.

Considering organisational culture as a factor in big data, we hypothesised (H3) that organisational culture positively affects BDS or big data systems. However, our results show that organisational culture had a positive but insignificant influence toward BDS ($\beta = .124$, $t = 1.326$, $p = .185$), OC effect on BDS was also small ($F^2 = .015$). Hence, hypothesis H3 was not supported. Generally, the effect size of organisational culture on BDS is low, and the same was observed.

Besides system quality, we hypothesised (H4) that organisational culture positively affects big data performers, including IT staff and data scientists. We discovered that organisational culture had positively and significantly influenced BDP ($\beta = .381$, $t = 4.705$, $p < .001$), with a moderate effect size ($F^2 = .17$), which means that H4 was supported.

In addition to the Big data performers and system quality, we hypothesised that organisational culture positively affects big data tasks (H5), including storing, analysing, and visualising. However, we noticed that organisational culture had an insignificant but positive impact on these big data tasks ($\beta = .149$, $t = 1.548$, $p = .122$), with a small effect size ($F^2 = .021$). Therefore, hypothesis H5 was not supported.

Furthermore, we hypothesised that organisational culture positively affects big data-enabled decision-making (H6). However, our results indicate that organisational culture positively influenced DES ($\beta = .017$, $t = .225$, $p = .822$) with no effect size ($F^2 = .000$). Moreover, OC effect on DES was not significant as well. Therefore, we conclude that H6 was not supported.

Besides the decision-making, we hypothesised that organisational culture would also positively impact organisational performance OP (H7). Results showed that H7 was supported since we observed a significant positive impact of OC on OP ($\beta = 290$, $t = 2.991$, $p <= .003$), with a moderate effect size of OC on OP ($F^2 = .110$).

In hypothesis 8, we proposed that BDS would have a positive effect on DES, as shown in Table 6.11 that BDS did have a significant positive effect toward DES ($\beta = .343$, $t = 4.811$, $p < .001$), BDES also had a small effect size ($F^2 = .110$), meaning that H8 was also supported.

Hypothesis 9 anticipated that BDT would impact the DES positively. However, although the results of the data analysis showed that BDT had a positive and significant influence on DES ($\beta = .274$, $t = 2.425$, $p = .016$), BDT also had a small effect on DES ($F^2 = .092$), meaning that H9 received significant support.

We then had a hypothesis (H10) which described that DES could influence the organisational performance in a positive manner. Data analysis revealed that DES positively and significantly influenced OP ($\beta = .377$, $t = 3.852$, $p < .001$). DES also had a moderate effect size on OP ($F^2 = .186$), which confirmed that H10 was duly supported.

Lastly, we hypothesised that BDP would have a positive impact on DES. However, the data analysis findings demonstrated that BDP had an insignificant but positive impact on DES ($\beta = .094$, $t = 1.266$, $p = .206$), with an ignorable effect size of BDP on DES ($F^2 =$

.010). Therefore, since the BDP impact on DES was insignificant, it was concluded that H11 was not supported.

6.5.2. Structural Model Quality Assessment

With path estimates, t and p-values, and effect sizes, we must assess the quality of the structural model as well, which can be determined with the help of predictive power, i.e., R^2 and predictive relevance of the model, i.e., Q^2. A synopsis of the R^2 and Q^2 estimates has made available in Table 6.11 below.

The R^2 estimate or the determination coefficient denotes the path model's prognostic power (in sample), i.e., the extent of variance in the outcome variables caused by the predictor variables associated with them," with higher values indicating more predictive accuracy (Hair et al., 2017). Besides predictive accuracy, the experiment was conducted with the subject blindfolded and at a predetermined distance. (D) equal to 7 to determine the model's predictive relevance. As we can note from Table 6.12 that 20.6% of OC, 26.2% of BDP, 25.6% of BDS, 18.6% of BDT, 33.4% of DES and 28.2% of OP has been explained by the overall model. The model returned the Q^2 values starting from 0.005 to 0.15. As per Hair et al. (2017), "Q^2 estimates > 0 for a reflective predictor variable emphasises the importance for making predictions of a path model for a particular outcome variable" (p. 202). The model had small predictive relevance for OC (Q^2 = .11), BDP (Q^2 = .08), BDS (Q^2 = .07), BDT (Q^2 = .05); and moderate predictive relevance for DES (Q^2 = .15) and OP (Q^2 = .14). Overall, the Q^2 values in Table 6.12 indicate that the path model in Figure 6.7 had small to moderate predictive relevance for included endogenous variables.

GOF "goodness of fit" is another method to evaluate the quality of structural models; GOF can be determined by the product of convergent validity and effect size (Tenenhaus et al., 2005). GOF criteria is to have positive values between 0 and 1. GOF is calculated by taking the square root of commonality yield and R^2. GOF values for the study model were all positive, with 0 to 1, which confirmed that the structural model had good overall fit and met the quality standards. Additionally, multicollinearity was also assessed for the structural model. The presence of multicollinearity can inflate the standard type II errors in bootstrapping, or it can cause failure in detecting the effect that would be present in the research (Hair et al., 2017). VIF estimates > 3.3 can indicate the pathological collinearity and contamination of the model (Kock, 2015). Table 6.12 confirmed that for each block of predictor and outcome variables had no collinearity issues (Garson, 2012).

Table 6.12. Coefficient of Determination and Predictive Relevance

Variable	Q^2	R Square	AVE	GOF	VIF
OC	0.11	0.206	0.514	0.325	1.500
BDP	0.08	0.262	0.544	0.378	1.503
BDS	0.07	0.256	0.519	0.365	1.388
BDT	0.05	0.186	0.520	0.311	1.419
DES	0.15	0.334	0.587	0.443	1.337
OP	0.14	0.282	0.550	0.394	1.396

6.6. Structural Model Robustness

This can be done through heterogeneity, non-linearity and endogeneity in PLS-SEM model (Hair et al., 2019; Sarstedt et al., 2019).

6.6.1. Nonlinear Effects (Quadratic Effects)

A mirage effect occurs when a relationship is considered linear but actually non-linear, or in other word this robustness check is related to the linearity of the data in the study model. To rule out the possibility of any such mirage or fulfil the assumption of linearity, we conducted the quadratic effects test by creating the interaction terms predictor variables with their self, as shown in Table 6.13. We utilised bias-corrected bootstrapping with 5000 samples (Shmueli et al., 2019), which indicated that most of the quadratic/nonlinear effects were insignificant, which was further confirmed by the values of T statistics. We also referred to F^2 values and found that all F^2 were greater than zero or positive (Cohen, 1988). So, based on non-significance and ignorable F^2 values, we concluded that the majority of the relationships in our model were linear and did not hold any quadratic effects. Thus our model is robust in terms of linearity, see Table 6.13 and Figure 6.8.

Table 6.13. Quadratic Effects

Variables	Estimate	T	P	F2
BDP x BDP → DES	0.061	1.558	0.120	0.022
BDP x BDP → BDS	0.106	4.331	0.000	0.072
BDP x BDP → BDT	0.051	0.978	0.328	0.014
OC x OC → BDP	0.085	1.753	0.080	0.025
OC x OC → BDS	0.141	3.525	0.000	0.069
OC x OC → BDT	0.097	1.578	0.115	0.028
OC x OC → DES	0.089	2.146	0.032	0.023
OC x OC → OP	-0.074	0.976	0.329	0.017
BDS x BDS → DES	0.049	1.129	0.259	0.007
BDT x BDT → DES	-0.109	0.947	0.344	0.041
DES x DES → OP	0.012	0.123	0.903	0.001

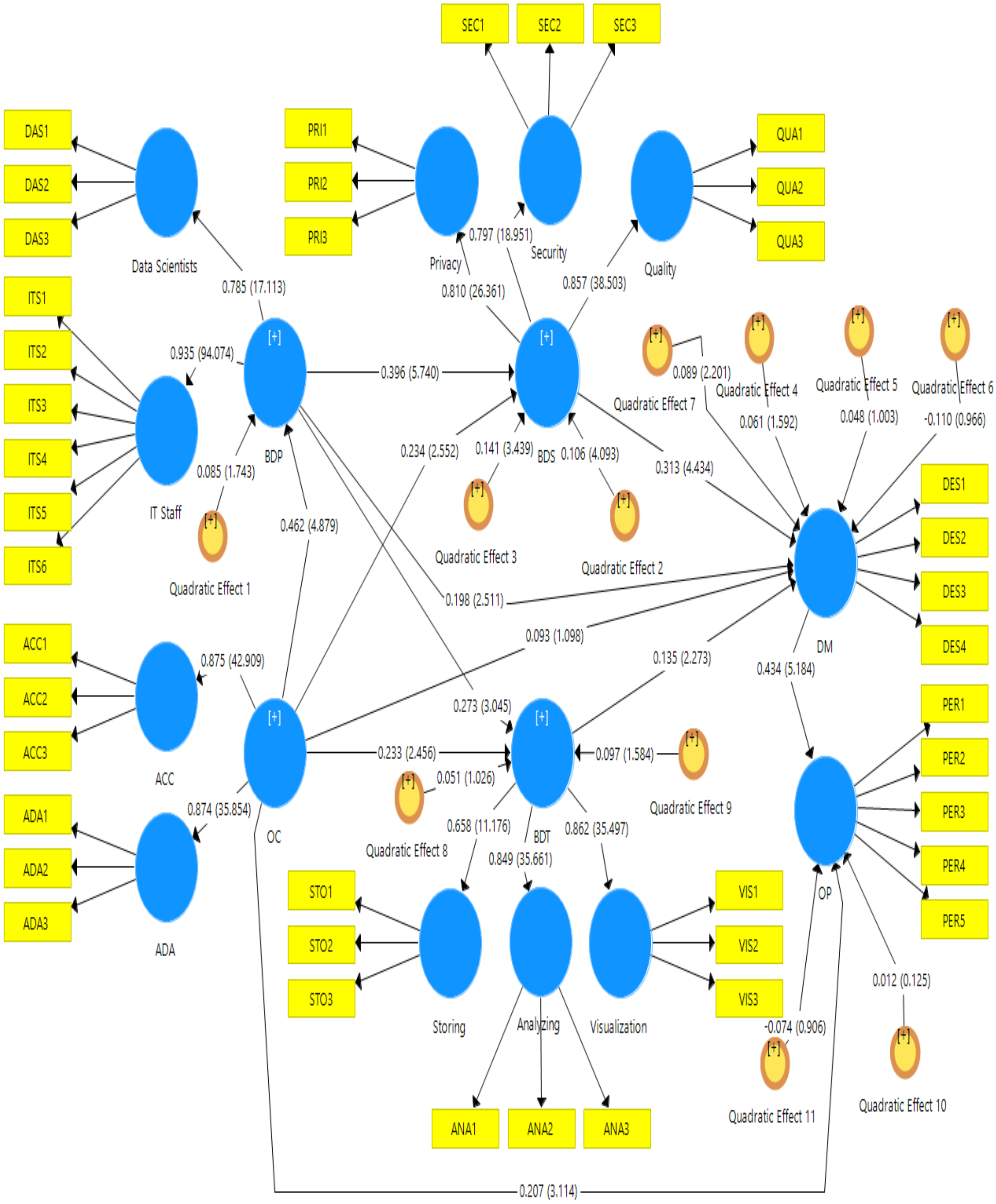

Figure 6.8. **Quadratic Effects**

6.6.2. Unobserved Heterogeneity (FIMIX-PLS)

We utilised FIMIX in SmartPLS to evaluate the robustness of the structural model with respect to unobserved heterogeneity. This means that no variables in the model can be further divided into additional variables (Shmueli et al., 2019). Therefore, the first thing was to assess how many segments the current model can have, for which we utilised the number of arrowheads directing towards a construct (dependent variable) which was 4, i.e., on DES. Therefore, the smallest sample required was 41, based on the 5% significance level and 80% statistical power (Cohen, 1992; Hair, Hult, Ringle & Sarstedt, 2021). Thus, based on the smallest sample size, i.e., 41, we could have a maximum of six (6) segments in our data (i.e., 270 / 41 = 6.58). However, considering the model complexity, we utilised a one-to-five-segment solution because an exactly equal distribution of the observations is practically almost impossible because an equal distribution of the observations must require the minimum samples in each segment – which is highly unlikely the case. Thus, FIMIX-PLS was run to assess the two to five segments' solutions.

Considering the above FIMIX carried out with 5000 iterations and with other default settings. Results were kind of ambiguous and conflicting as Akaike's information criterion (AIC), Modified AIC with Factor 3 Modified AIC with Factor 4 (AIC4),Hannan-Quinn Criterion (HQ), Bayesian Information Criterion (BIC) and LnL (LogLikelihood) suggested a 5-segments solution shall be the best to be considered. 5-Segment was candidly supported by the best-performing criteria, i.e., AIC4 and BIC (Ringle & Schwaiger, 2020), so a 5-Segment solution was the strongest candidate for this model. On the other hand, minimum description length with factor 5 (MDL5), EN (normed entropy statistic), NFI (non-fuzzy index), and NEC (normalised entropy criterion) were in favour of 2 segments solution. MDL5 is known for underestimation issues related to the number of segments (Sarstedt et al., 2011); therefore, it was a weak candidate for this model's segment solution. Any selection criteria did not support 3-Segment and 4-Segment solutions, so those were not potential candidates. See Table 6.14 for details.

Table 6.14. Fit Indices and Relative Sizes for Segment Solutions

Criteria	**Segment**				
	1	**2**	**3**	**4**	**5**
AIC	7895.17	4821.29	4258.16	4082.83	***3884.90***
AIC3	7931.17	4894.29	4368.16	4229.83	***4068.90***

AIC4	7967.17	4967.29	4478.16	4376.83	***4252.90***
BIC	8024.72	5083.97	4653.99	4611.80	***4547.01***
CAIC	8060.72	5156.97	4763.99	4758.80	***4731.01***
HQ	7947.19	4926.77	4417.11	4295.24	***4150.78***
MDL5	8830.89	***6718.71***	7117.29	7903.67	8667.45
LnL	-3911.59	-2337.64	-2019.08	-1894.42	***-1758.45***
EN	-	***1.00***	0.95	0.93	0.95
NFI	-	***1.00***	0.96	0.93	0.94
NEC	-	***0.01***	12.74	18.78	14.48

We referred to the relative segment sizes to confirm that potential segment solutions have adequate sample sizes (Table 6.15). Considering the high compliance with the selection criteria, we first considered the 5-Segment solution and found that it yielded only 29 observations (.109 x 270 = 29.43) which were way less than the minimum required sample size, i.e., 41, so the 5-Segment solution was ruled out. While in the 2-Segments solution, segment-2 yielded a sample size of 68 observations (.252 x 270 = 68.04), which met the minimum sample size, but MDL5 underestimated the segment solutions. Therefore, researchers should extract more segments from the MDL5 offered solution (Hair et al., 2016), which indicated that we needed a divergent segment solution instead of a specific one. Hence, we looked at the other segment solutions and found that the 1-Segment solution has the maximum sample size in any solution, while 2-Segment and 3-Segement also meet the minimum sample criteria. Consequently, we had a divergent and ambiguous segment solution.

Given this scenario where we can go for a 1-segment or multi-segment solution, it can be finalised that unobserved heterogeneity was not significantly affecting the data (Sarstedt et al., 2017b). Taken together, we concluded that the FIMIX analysis did not explicitly provide a precise segment solution. Therefore, data showed no significant levels of unobserved heterogeneity, so the robustness of the results was evident.

Table 6.15. Segment and Yielded Sample Size

Relative Segment Sizes (*N = 270*)					
Segment	**1**	**2**	**3**	**4**	**5**
1	1				
2	0.748	0.252			
3	0.423	0.332	0.244		
4	0.312	0.273	0.244	0.171	
5	0.278	0.244	0.196	0.172	0.109
Yielded Sample Sizes (*N = 270*)					
1	270.00				
2	201.96	68.04			
3	114.21	89.64	65.88		
4	84.24	73.71	65.88	46.17	
5	75.06	65.88	52.92	46.44	29.43

6.7. Importance-Performance Map Analysis (IPMA)

The IPMA, is a critical evaluation in PLS-SEM, allowing us to gain more insights from the path model. While the path estimates exhibit the importance of variables, the IPMA will show the performance of those variables and their indicators. The IPMA compares the total effect, i.e., (importance) & mean value of the predictor score (i.e., performance) using a graph (i.e., the importance-performance map). The map identifies high-priority factors or areas that call for management attention. Such areas are represented by variables with high importance but low performance. In this study, we run IPMA for two critical outcome variables, i.e., decision-making (in Figure 6.9) and organisational performance (in Figure 6.10).

As shown in Figure 6.9, all direct constructs connected to big data-enabled decision-making (i.e., OC, BDP, BDS and BDT) had high performances in driving decision-making with the highest effect (important) and high performers as well. Then we had BDP, which also had a large effect on DES and was the highest performer among all variables. BDT had a moderate- effect on DES, but still it was high performing predictor. Finally, OC had moderate importance for DES (perhaps due to non-significant impact in hypothesis testing), but somehow its performance was higher than BDT.

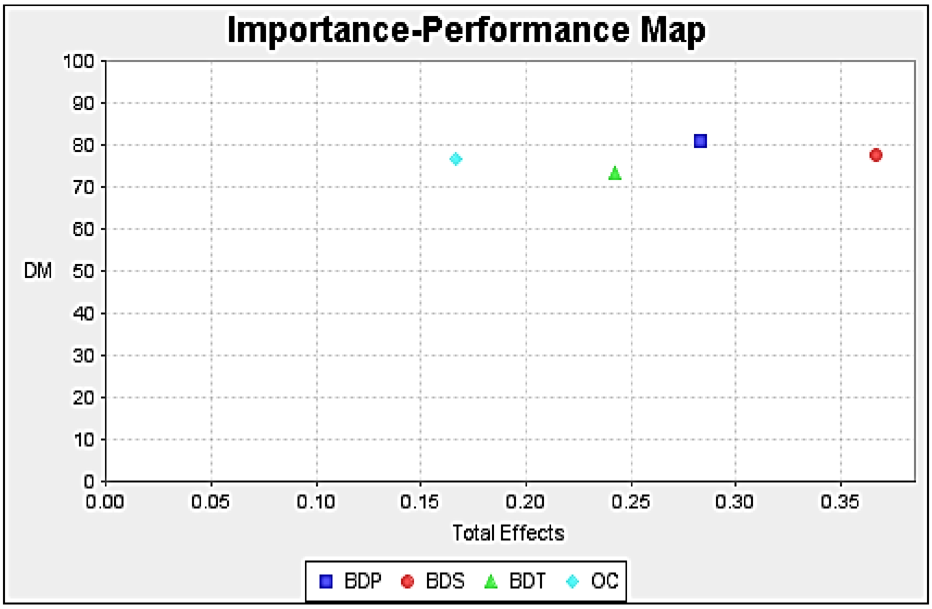

Figure 6.9. **IPMA Map for Decision Making**

As shown in Figure 6.9, 6.10, both DES and OC had a high performance in driving organisational performance; they also had large effects (i.e., high importance) on DES. However, DES was the leader among the two variables as it had high importance and high performance for the DES simultaneously. Nonetheless, OC was barely behind the DES; OC also had a large effect (high importance) on high performance in driving the DES.

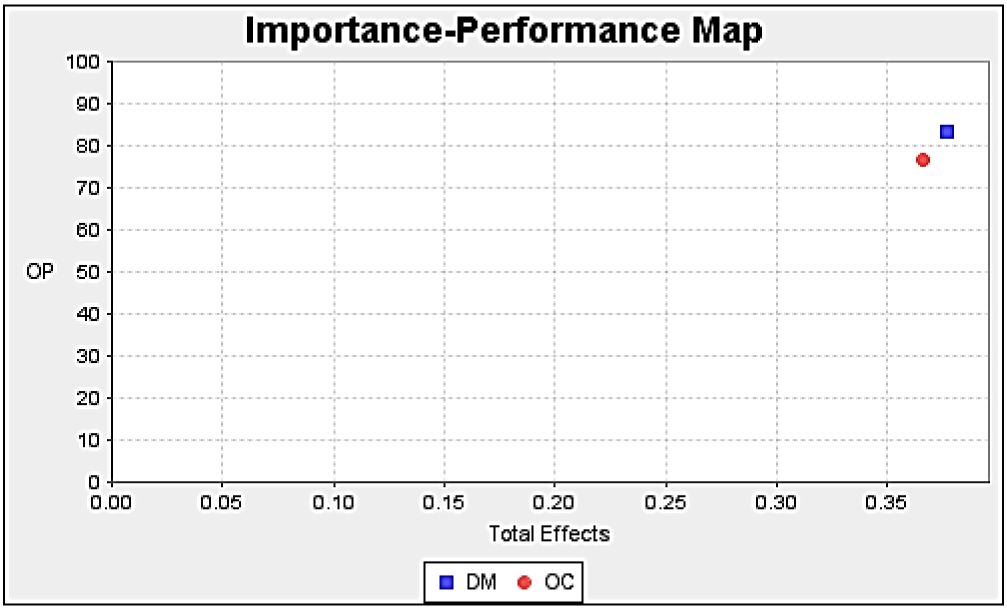

Figure 6.10. **IMPA Map for Organisational Performance**

Chapter 7

Qualitative Data Analysis: Thematic Analysis & cross-case Analysis

7.1. Introduction

This Chapter analyses the theoretical concepts illustrated in Figure 3-1 in Chapter 3. Our research phenomena are critically examined using a theoretical thematic. Besides the theoretical theme, we applied cross-case analysis. This analysis allows us to examine the differences and similarities among the themes and their interrelationship. The following Chapter offers a synthesis of findings to put the findings into context and relate them to findings from previous chapters. The Chapter begins with pretesting of the interview processes, cases included in this study, and their explanations. Then, participants of the qualitative method were discussed, followed by the themes & Categorical and across cases analysis.

7.1. Pretesting Interview Questions

A thorough study needs an exhaustive review of the interview questions; thus, the researcher completed an exhaustive evaluation before settling on the number of questions to work on in each phase. The committee members, experts, and academic staff in Saudi universities were the primary users of this study's evaluation process. The reviewers were four, and all of them work in the education sector. One of the experts was female. Three reviewers were male. The reviewers aged from 29 to 40 years. All expert reviewers were sent interview questions containing the current round's questions for the initial evaluation. The expert reviewers then examined the questions, and the reviewers provided ideas to improve them. The author altered the interview questions to add to the expert reviewers' suggestions. Iterations, following a period of review where the iterations are examined for the interview, provide feedback that accommodates reviewers, for example, by providing question types that are not likely to elicit a leading response. Finally, the expert reviewers approved the questions, and data collection began. Figure 7.1 illustrates the process of the pretesting for interviews.

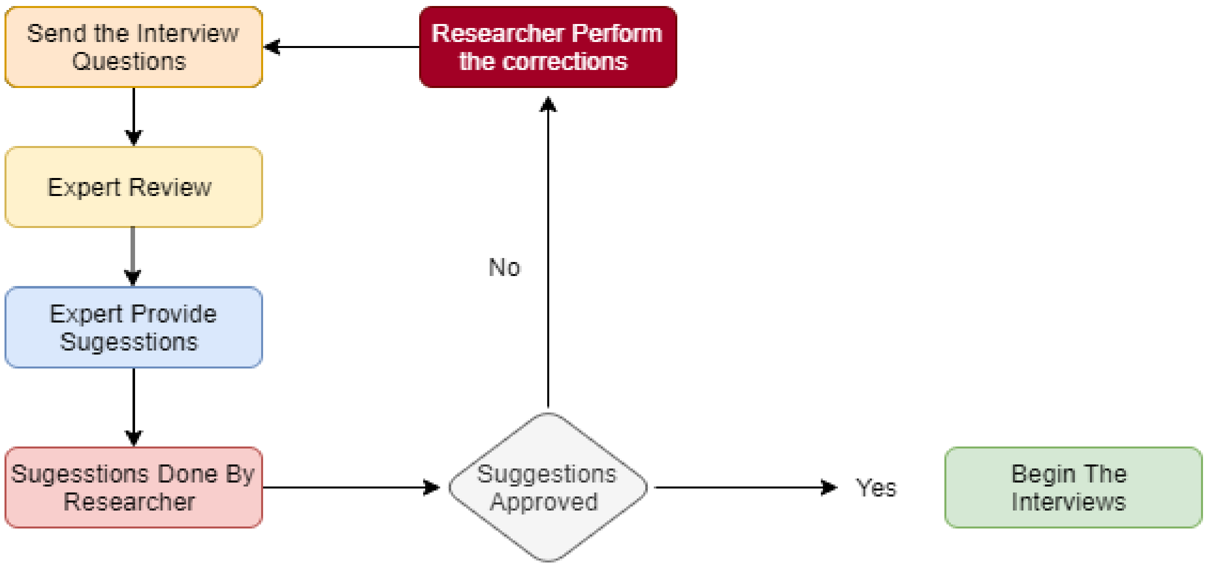

Figure 7.1. **Pretesting process for qualitative study.**

7.2. Cases Description

As discussed in chapter 2, that includes the research context, specifically Saudi Arabian universities. The researcher considered six universities within Saudi Arabia, which were categorised based on their location within Saudi Arabia. The first university is located in the Northern Part of the country, which we named Northern University 1(NU1). The second university is located in the southern country, and we named it Southern University 1(SU1). Third is Western University 1(WU1). The fourth institution is Eastern University1 (EU1). The Fifth explored university is located in the middle of Saudi Arabia, and the researcher Labeled it as Middle university1 (MU1). The last university is categorised as the Western Northern Part (WN1). The researcher conducted two interviews from NU1, four interviews from SU1, three interviews gathered from WU1, two from EU1, and three participants from MU1. Lastly, the researcher interviewed three participants from WN1. Table 7-1 briefly describes cases utilised in the current study.

Table 7.1. **Number & Descriptions of cases**

Cases		Number of conducted interviews
No	ID	Two Participants
1	NU1	
2	SU1	Four Participants
3	WU1	Three Participants
4	EU1	Two Participants
5	MU1	Three Participants
6	WN1	Three Participants

NU1 is the first case among the cases in our study, and it is located in the Northern part of the country. This is a governmental public university that started over 15 years ago. It has five colleges, and it provides educational services to the citizens. The university has more than 2000 staff, including academic and non-academic. The university implemented an intelligent system over 12 years, and it was among the first universities in their online learning system, which is considered one of the primary sources of big data.

SU1 is the second case of our study. This university was also established over 15 years ago, and it is located in the Southern part of the kingdom. The university has more than 60,000 enrolled students. The university has more than five campuses in different locations within the region. It provides educational services to the community in various majors. The university started the implementation of innovative systems to support the country's vision of 2030, as well as achieving the university's goals to be the leader of information technology innovation within the region.

WU1 is the third university in this research, and it was established over 19 years ago. WU1 is considered a big university since it has more than 28 colleges and seven campuses. The university has more than 2000 international students and plans to increase the number aligning with the country's vision of 2030. WU1 is well known for its Islamic courses in Saudi universities. In addition, WU1 started to provide short online courses during the lockdown of COVID-19 as community services. The university has various systems for the university data, statics, and a data centre.

EU1 is the fourth higher education institute and is considered a medium-sized university. It has been serving and providing educational assistance for more than 12 years. The total number of enrolled students is 5000, 67% are local, and 33% are from other nations. EA1 is familiar with its medical college and is considered the first university in medical science among Saudi universities. The university has various sources of data analysis. The university is fast-growing in Information and Communication Technology and supports new technological improvements.

The second last university is MU1, a medium university since it has more than 62,000 students and more than 6000 staff. The university was founded more than 40 years; it has more than 14 colleges, 70 scientific institutes within the country, and five overseas. The university is developing new information systems to improve the university systems aligning with the kingdom vision 2030. In addition, the university has provided Islamic educational services since it was an institute of Islamic studies.

WN1 is the last higher education institution in the current research. WN1 is located in the northwestern part of the country. It was founded over 12 years ago. The university has more than 32,000 students and 1980 academic staff. The university is considered a medium-sized university since it has more than 14 colleges in various disciplines located in different locations within the country. WN1 is considered a young university and aims to be the leading university in information technology, and it has collaborated with overseas universities to improve the information technology centre within the university.

7.3. Participants

This study targeted the knowledge workers (data scientists) and IT staff within Saudi Arabian universities. IT staff can be categorised as academic and non-academic staff. It should be noted that no scientific sampling is required for the current study—however, similar studies were conducted from 8- to 12 interviews. (Huang et al., 2013; Okoli & Pawlowski, 2004). Expert participant withdrawal could be an issue due to the iterative nature of the procedure, as suggested by Keeney et al. (2006). As a result of having a great deal of expertise, the research participants may not be able to participate in the study as it occurred during the invitation process (Skulmoski et al., 2007). Thus, this study used a sample size of 17 detailed interviews to avoid missing anyone, which was determined to be appropriate. Table 7-2 summaries participants' demographic information.

Table 7.2. **Participants' demographic information**

ÍD	University's size	Participant Age	Gender	Years of Experience	Current Role
NU1a	Small	42	Male	13	Dean of IT Department, academic staff, one of the decision-makers within the university
NU1b	Small	52	Male	25	Dean of E-learning, Head of IT quality assurance.
SU1a	Medium	34	Male	5	Dean of Information Technology and Distance Learning, Top Management Staff (decision Maker)
SU1b	Medium	35	Male	8	IT security, Dean of Admission and Registration
SU1c	Medium	42	Male	15	IT Manager.
SU1d	Medium	37	Male	10	Cybersecurity, Developer, Head of IT facilities and data visualisation
WU1a	Big	35	Male	3	IT Manager, Head of Educational centre, Data Security.
WU1b	Big	43	Male	10	Data Scientist, Academic Staff.
WU1c	Big	37	Male	10	Academic staff, Assistant Dean

EU1a	Medium	57	Male	35	Vice president of Strategic planning and scientific Research, Decision Maker (Top Management Staff)
EU1b	Medium	40	Male	12	IT manager, Head of Data security, Data engineer
MU1a	Big	39	Female	12	Dean of IT services, Data scientist, Decision Maker
MU1b	Big	40	Male	8	IT senior staff, information security specialist
MU1c	Big	29	Male	6	Data Privacy, security.
WN1a	Medium	35	Female	11	Academic staff, Assistant Dean at IT Deanship
WN1b	Medium	32	Male	5	Academic staff, manager of the data centre.
WN1c	Medium	34	Male	11	Data Engineer

7.4. Themes & Categorical and across-cases analysis.

Our prime analytical concern is summarised in figure 7-1, which links it with proposed research questions, aims, and variables. First, the researcher examines BDP (human) factors in big data security, privacy, and quality; see sections 7-5. Second, we discuss the influence of BDP on big data tasks, including storing, analysing, and visualising. Third, we explore the impact of organisational culture on human and technical aspects- see sections 7-6. Third, we investigate the importance of big data systems and their impact on improving executives' decision-making in Saudi universities see sections 7-7. Fourth, the researcher explores the influence of big data tasks on improving the decision-making by top management- see section 7.8. Lastly, we examine how BDA can improve the university's performance- see sections 7-9.

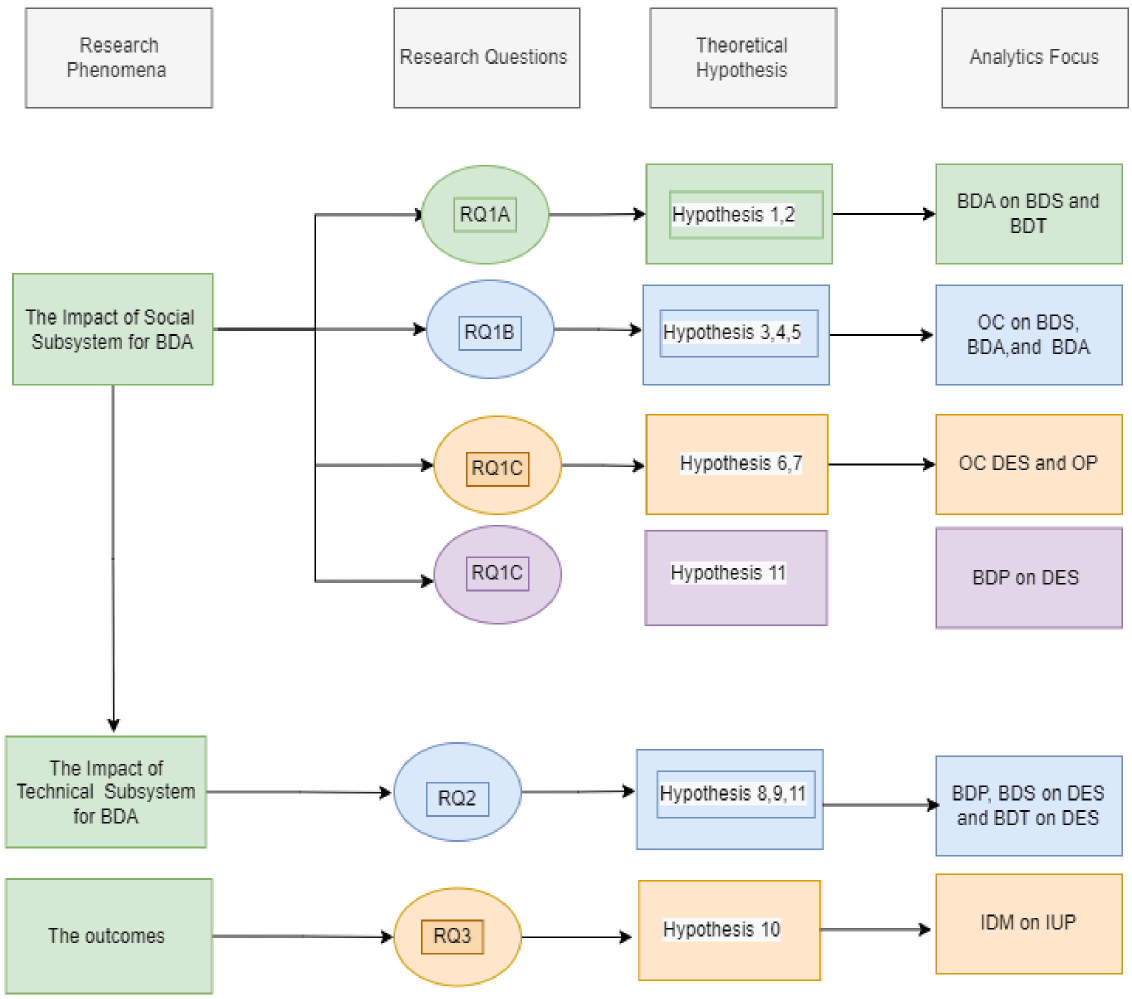

***Figure 7.2*. Linking analytical focus and research questions**

In figure 7.2, the authors propose the significance of human factors, represented in the current study as IT academic & non-academic staff and data scientists. For example, IT academic staff proposed to secure big data and maintain privacy in this study. Besides, data scientist is a crucial human aspect that makes good data quality that could enhance the decision-making by top management.

Organisational culture is also considered the social aspect that impacts BDP technical factors that could support the BDA. While the social aspect represented in this study evolves around human and organisational culture, technical factors in this study focus on the BDA system. This technical factor is the quality of BDS data systems, including big data security, privacy, and big data quality. These features in big data systems could improve decision-making since it allows the decision-makers to make decisions based on the secured- private and good quality of analysed data.

The second last analytical focus for research is big data tasks and their roles in improving the decision-making by executives. Those tasks include big data storage from different sources and ensuring those stored data could be improved. For instance, data storage from social media could assist decision-makers in making their decisions based on that stored data. The second important task included in big data tasks is data analysis, analysing the data that could help improve decision-making. The last step in big data tasks is the visualisation of analysed data, which includes different forms of analysed data that allow the executives to make effective decisions relying on the visualisation of big data tasks.

The last analytics focus in our study is improved decision-making leads to improve university performance in two factors. First, decision-making quality can improve academic performance and outcomes within the university. Second, enhancing decision-making by top management leads to creating business values for the universities that implemented BDA.

The theoretical model produced the topics according to the research framework in Figure 3-10 and our analytical priorities in Figure7-2. New and unpredicted conclusions unfolded from the data, as such findings emerged from the previously listed codes. The table to the right displays the total number of references and sources in Nvivo 12 Pro on the themes and categories.

The researcher then explored the most frequent words that occurred within the data. Those words allow the investigator to find the main patterns and insights of the collected data. Then the researcher gets the idea of creating the themes and categories of the data collected to understand the phenomena better. Below is the word cloud that includes word frequency.

Figure 7.3. **Words Clouds (frequency) of the collected data.**

Although all of the data was collected from educational sectors, the collected data results were beyond the researcher's expectations. Besides, the analysis of the cross cases was applied among these cases to identify the patterns, similarities, and differences within the cases. To pick the appropriate techniques for comparing the cases in our study, we followed the tactic used by Eisenhardt (1989); he stated that cross-case comparison could involve three tactics. The first is choosing the dimensions within one case and then finding the similarities and dissimilarities within the intergroup. The second tactic is to list two cases and the similarities and differences between each case. The third tactic is to categorise collected data by the source of data. For the current study, we follow the first tactic, where we classify the cases based on the nature of the university, as described in table 7-1. In the next section, we will discuss the themes and codes related to human factors represented in the current study as big data performers toward the security and privacy of big data.

7.5. Big Data Performers on Big Data Security, Privacy, and Quality

Big data performers in the current study are represented as IT staff for the security and privacy of big data and the data scientists responsible for the big data quality and big data tasks. In addition, we propose that big data performers and IT staff positively impact the security and privacy of big data, and data scientists positively impact the quality of big data and big data tasks. Considering the roles of big data performers, this section presents qualitative findings of the captured data of BDP.

7.5.1. First-Order Category of Big Data Performers

The results presented in this section answer research question 1 a**,** which asked about the significance of social factors, "big data performers", toward the security, privacy, and quality of big data. IT staff within Saudi universities have significant roles in securing big data and ensuring that the privacy of big data is taking place. Besides IT staff, data scientists are also considered important social "human" factors since they ensure that stored data is of good quality. Some participants mentioned the importance of social "human" factors in organisations. For instance, one participant from EU1

"IT staff in our university plays a vital role in big data system including security as well as big data quality EU1a."

Similarly, another Participant from WU1 mentioned that.

"In general, human factors in any organisation are important, but when you are considering the security and privacy of big data, it becomes essential because, in our data centre, we have faced "cyber-attack" since that time, we are aware of security and privacy of the system in general not only stored big data." WU1a."

Table 7.3. **Frequency of Codes across groups in Big Data Performers.**

First-order Category	Codes	Source	References	Code Prevalence
Big Data Performers	IT Staff for securing Big Data	10	19	30.89%
	IT staff for Privacy of Big Data	10	14	20.76%
	Authority of Cyber Security	8	11	11.5%
	Security Matters in General	3	3	6.85%
	Data Scientists Big Data Quality	10	10	30 %

Table 7-4 discussed the frequency of codes related to human factors, "big data performers"; these codes form BDA performers regarding big data security, privacy, and quality. The following table will discuss the observations of codes among cases under the category of big data performers.

Table 7.4. **Analysis of cross-cases First Order Categories of Big Data Performers.**

Case		First-Order category of Big Data Performers Among Cases				
		ITSs	ITSp	SACS	SG	DSQ
NU1	NU1a	√	√	√		√
	NU1b	√	√	√	√	√
SU1	SU1a	√				√
	SU1b		√			
	SU1c				√	
	SU1d			√	√	
WU1	WU1a	√	√	√	√	√

	WU1b	√	√	√		√
	WU1C		√		√	
EU1	EU1a	√	√			
	EU1b	√	√			
MU1	MU1a	√	√	√		√
	MU1b	√				√
	MU1c		√		√	
WN1	WN1a	√	√	√		
	WN1b	√	√	√	√	√
	WN1c	√	√			
Appearance of Categories in percentage		30.89%	20.76%	11.5%	6.85%	30%

√ – This symbol is the group of categories observed within cases. **ITSs –** IT staff for Security **ITSp** – IT staff for privacy. **SACS** - Saudi Authority for Cyber Security **SG –** Security in General **DASQ** – Data Scientists for Quality

As shown in table 7-4, human factors are represented in this study as big data performers; this category has been realised in six forms among our study cases.

NU1: the most form realised in the NU1 is IT staff for big data security, IT staff for big data privacy, data scientists for big data quality, and data scientists for big data tasks. The second higher form realised in big data performers is data scientists for big data tasks. The least observed forms are the Saudi authority of general cyber security and security matters within selected Saudi Arabian universities.

SU1: the most observed form in SU1 are IT, staff for big data security, data scientists for big data quality, and data scientists for big data tasks. However, IT staff for big data privacy, Saudi authority of cyber security, and general security matters have not been observed within SU1.

WU1: the most common forms observed in WU1 are IT staff for big data security, IT staff for big data privacy, and data scientists for big data quality. The second higher observed form within the WU1 is data scientists for big data quality. The least realised form within WU1 is security matters in general.

EU1: in EU1, IT staff for big data security and IT staff for big data privacy. However, the Saudi authority of cyber security, security matters in general, and data scientists for big data quality have not been observed in EU1.

MU1: the most observed in MU1 is the IT staff for big data security, IT staff for big data privacy, and data scientists for big data quality. The second higher observed form in MU1 is data scientists for big data tasks. The least realised for MU1 is security matters in general.

WN1: IT staff for big data security, IT staff for big data privacy, and data scientists for big data quality were the most realised forms in WN1. The second higher observed form in WN1 is the scientists for big data tasks. The moderately observed form in WN1 is the Saudi authority of cyber security. The least observed form in WN1 is security matters in general.

Following sections, we will discuss the forms of big data performers, their related codes, and references. The forms and related codes and references will be IT Staff for Security ITSs, IT Staff for Privacy ITSp, Data Scientists for Big Data Quality DSQ, Data Scientists for Big Data Tasks, Saudi Authority of Cyber Security SACS, and lastly, Security Matters in General SG.

The human factor is the central fundamental pillar within any organisation; in the current study, ITSs are crucial human factors in big data systems since they secure the system from external threats by monitoring the system and updating the firewall. Besides the roles in securing the system, ITSs control access to the big data system. In addition, ITSs report the current status of big data systems to the Saudi cyber security authority. Various references related to ITSs were realised across the studied cases. Below are the codes derived from ITSs

- Protecting stored big data (EU1a, EU1b SU1a, NUIb, NU1a, WN1a, WN1c)
- Controlling the access to big data system (NU1b, SU1a, MU1a, WN1c NU1a, WN1a, WN1b)
- Authorisation (NU1b, NU1a, SU1a)
- Policies related to changing passwords (NU1a, NU1b)
- Reporting to the Saudi authority of cyber security (WU1b, WN1a, EU1a, EU1b, MU1a)

- Protecting the system from external attack (WN1a, NU1b, SU1a)
- Authentication (EU1b, UN1a)

Regarding the first codes derived from ITSs, Participants from various cases mentioned that

"We have our teams, and they have experience in information security for protecting our stored data from university and other different resources EU1a". MU1a also stated, "In my university, the role of IT staff is to secure the whole system that stores big data MU1a."

Another participant also stated that

"Information system employees, whether academic or non-academic staff, participate in protecting big data; they secure the data. Nevertheless, the academic staff they not fully engaged the big data security. Therefore, we are relying on non-academic staff for big data security and privacy WN1a".

Similarly, a Participant from WN1b mentioned that,

"The role of ITSs for big data security allows the university to secure the data from external attack" WN1b.

A participant from EU1b, who is working as an information security engineer, mentioned that,

"In my university, IT academic staff play an important job in securing the university system as the whole and big data system we have a monthly and weekly report on the security status".

IT staff for big data privacy is the second form of big data performer. ITSp for big data privacy is seen as the main factor in protecting the personal information that might allow others to identify the person, i.e., information about the person that can affect the decision made by the decision-makers. Therefore, it works hand in hand with the system to ensure that stored data is private. Besides, the IT staff needs to apply standard policies regarding big data to ensure it is private. The following codes have been derived from ITSp.

- Collected data is private (MU1a,SU1a, UN1a,EU1a,WU1a)
- Protecting personal information (NU1a,WN1a,WU1a, WU1a,EU1a, WN1c)

- Applying Standard policy for data privacy (NU1a,MU1a,b,WN1a,WU1a)

Participants from different cases have mentioned that ITSp plays a vital role in ensuring big data privacy is applied when dealing with big stored data. For instance, one participant claimed that

"The system does not allow anyone to know the data that has been collected belonging to whom or who is the owner of some of the data collected WU1a".

Similarly, another participant also mentioned that

"The same thing applies to privacy where IT staff ensure that there is no information that can lead to identifying the person of collected big data WU1a."

Regarding applying standard policy for data privacy, Participants highlighted that,

"The IT staff's current role in applying standard policy is ensuring that the collected big data related to people or sensitive data is private UN1a."

The third category of big data performers is Data Scientists for Quality of big data DSQ. Big data has attracted researchers to investigate the significance of BD more profoundly. However, big data quality is crucial when organisations start developments related to big data analytics to achieve a firm's goals. In such a scenario, data scientists in each organisation play vital roles in ensuring the quality of collected data is aligned with the organisation's objectives. Participants mentioned various points regarding data scientists' significance in making useful analysed data for top management's best decisions. Saudi selected universities, for example, realised the importance of data scientists on the quality of analysed data. The following codes and references are derived from the interviewees.

- Standard of data Quality (WNU1a, WNU1b)
- Data scientists and data quality (UN1a, EU1a, EU1b,WNU1b,SU1a,WU1a,UN1b)
- Data quality and decision quality (SU1a, NU1a)
- Third-party data scientists (EU1a, EU1b)

From the codes and references discussed above, participants from the different cases stated their opinions and experiences about the roles of data scientists related to data quality. For example, participants from the case WNUa, WN1b stated that

> "What I noticed recently has become an official job as a data collector or a scientist. It has become a recognised job and has a job title. It was just that it collects data and provides it, but I am interested in the issue of data quality from the side of development and quality, that data scientists should be aware of the standard of data quality" WNU1b.

Similarly, a Participant from the same university (case) also mentioned that

"There is no specific assessment of how the required quality is determined. However, they should be standard for the data scientists to determine whether this is good or bad quality" WNU1b".

For the role of data scientists and data quality, most participants agreed that data scientists are the main factors for making a good quality of analysed data. For instance, one participant stated that

"Data scientists' first role in the university is to ensure that the data is of good quality and can lead the decision making to make the decisions that come from good quality of data. How to identify the quality of data by knowing the current concern of top management and the areas that need improvements within the university and based on that data scientists analysed the data and provided it to top management staff to make their decisions NU1a".

Besides, one participant emphasised data scientists' significance in big data quality. The interviewee mentioned that

"Data storage is considered an initial stage to start the analysis process. I mean, if we go through a stage, one of the basics is to pay attention to the quality of the data because if the data is of poor quality, it would negatively affect the objectives for which it was analysed, and this is the job of data scientists MU1a".

The last derived codes and references under the category of the data scientists toward data quality are their university hiring data scientists by third party outsourcing". As an example, participant EU1a asserted that

"We have third-party data analysis staff and data scientists for ensuring the quality is taking place EU1a".

Similarly, EU1b highlight that

"Currently, we do not have data scientists for data quality, but we do some data analysis tasks. However, the university has a contract with a third-party company to perform these tasks EU1b".

Saudi Authority of Cyber security SACS is the fourth form of big data performer. This form unfolded during the qualitative data collection; the code revealed that the Saudi authority of cyber security is the Saudi Arabian Governmental Agency responsible for securing governmental organisations. Besides, SACS is considered an essential human factor since the people working in SACS, besides the IT staff's role in big data security and privacy within the selected universities, report the security status of the system of big data. Therefore, the following codes have been obtained from SACS.

- IT staff and SACS (WN1b, EU1a, NU1b)
- Reporting to SACS (EU1a, WN1a)
- Standard of Security and Privacy in Selected Universities (EUa1, WU1a, NU1b)

Various participants have claimed that IT staff in selected universities and SACS staff collaborate to ensure that stored data is secured and private. As a participant from EU1a stated that

> "There is a specific standard from the Deanship of information technology departments that communicate directly with the Cyber Security Authority in the Kingdom EU1a".

Participant also mentioned that IT staff reports about the current status of the system's security, i.e. are there any common threats,

"The team works with cyber security authorities for security purposes and reports if there are any suspicious activities in the big data system to SACS EU1a".

In addition, Participants have also stated that

"There is another role being checked by the Saudi Authority of cyber security; it is responsible for the whole university data in terms of security and privacy" NU1b.

Security matters in General SG occurred during the coding of the interviews as the lower codes have been mentioned with the interviewee. In addition, the interviewees mentioned other security matters, such as the department or deanship, which are responsible for the security and privacy of the system. Participants also mentioned that they had applied two authentication factors to increase security. When accessing the system, those processes are applied to the students and staff; he believes "the interviewee" will increase the university's security. The following codes are derived from the participants regarding the security matter in general.

- IT deanship or departments for data security within universities (SU1a, WU1a)
- Increasing security matters (EU1a, WU1a)

Considering the above codes derived from the interviews, Participants mentioned that there are independent departments and deanship for technical matters such as maintaining the system and applying various procedures to improve the system's security.

"We have our department in deanship of information technology responsible for technical issues such as security" SU1a.

Similarly, a participant from WU1a stated

"There is a unit in the IT centre responsible for the security verification of the system itself, in general, the whole university system WU1a".

However, a Participant from EU1b mentioned that to increase the security in our university, we have applied two-factor authentication to the student and the staff. He also stated that

"Recently, we have applied two factors authentication when accessing the system for staff and students EU1b".

7.6. Big Data Performers on BDT

Big data performers in this study are delineated as IT staff and data scientists for big data analytics tasks. Besides, we proposed that big data performers positively impact big data analytics tasks that include storing, analysing and visualising big data for improving top management decisions. In the light of the roles of big data performers, this section presents qualitative findings of the data being collected related to big data performers.

7.6.1. First-Order Category of Big Data Performers on BDT

The results presented in this section answer research question 1 a, which sought the significance of social factors "big data performers" toward the big data tasks, including storing big data from various sources, analysing it, and visualising it for better decisions by top management of Saudi Arabian higher education. Participants from different studied cases provided their opinions on the impact of BDP, namely, data scientists, on big data tasks. The following table discusses the frequency of codes across the studies cases.

Table 7.5. **Frequency of Codes across groups in Big Data Performers**

First order Category	Codes	Source	References	Code Prevalence
Big Data Performers	Data Scientists Big Data Tasks BDT	15	22	80 %
	Data Engineer	9	15	8.8%
	IT staff	3	11	11.02%

Table 7.5 discussed the frequency of codes related to human factors, "big data performers"; these codes related to BDA performers, precisely the significance of big data performers on big data tasks. The following table will discuss the observations of codes among cases under the category of big data performers.

Table 7.6 Analysis of cross-cases First Order Categories of Big Data Performers Data scientists on BDT.

Table 7.6. **Analysis of cross-cases First Order Categories of Big Data Performers (Data Scientists on BDT).**

Case		**First Order category of Big Data Performers Among Cases**		
		BDT	**DE**	**DAS**
NU1	NU1a	√		√
	NU1b	√		
SU1	SU1a	√		√
	SU1b	√		√
	SU1c	√		√
	SU1d		√	
WU1	WU1a	√		√
	WU1b			√
EU1	EU1a	√	√	
	EU1b		√	
MU1	MU1a	√	√	
	MU1b			
	MU1c	√	√	√
WN1	WN1a	√		√
	WN1b	√		√
	WN1c		√	√
The appearance of Categories in percentage		60%	8.8%	11.2%

√ – This symbol is the group of categories observed within cases. **BDT –** Big Data Tasks - DE- Data Engineering. **DAS**- Data Scientists

The table above shows the revised codes among the cases in our study. These cases and their related codes will be discussed below.

NU1: The most prominent form realised in the NU1 is BDT, The second higher form realised in big data performers are data scientists for big data tasks. Data scientists' roles in big data tasks are the least observed forms. The last observed code is the role of a data engineer in big data tasks. Although this code was realised during the interviews, it was not proposed in our research model.

SU1: the most observed form in SU1 is data scientists for big data tasks. However, data engineer for big quality and big data tasks has not been observed within SU1.

WU1: the most common forms observed in WU1 are data scientists for big data tasks. The second higher observed form within the WU1 is big data tasks that include storing big data, analysing, and visualising big data for better decisions. Nevertheless, data engineer has not been observed in the case of WU1

EU1: in EU1, data engineer for big data tasks is the higher-realised form. The second form is big data tasks. However, data scientists have not been observed in EU1.

MU1: the most observed in MU1 is the BDT. Where data engineer is seen as the second higher realised form in MU1. However, data scientists have not been realised in MU1

WN1: big data tasks were the highest form noticed in WN1. The second higher observed form in WN1 is the scientists for big data tasks. However, data engineer has not been observed in WN1.

In the next sections, we will discuss the forms of big data performers (data scientists and big data tasks) that include storing, analysing, and visualising big data. In previous research, data scientists are seen as the main factors in gaining advantages in analysing big data. Some scholars believe that data scientists should be responsible for analysing the data to gain new patterns and insights that could help organisations achieve their financial and strategic goals. On the other hand, some believe that data scientists should be responsible for storing, analysing, and visualising big data to achieve different goals. Similarly, in the current study, some of the participants believe that storing the data is not the responsibility of the data scientist; it should be the data engineering responsibility. The following codes and references were obtained from participants.

- Big data tasks (NU1a, WU1a, MU1a, EU1a, SU1b , SU1c,NU1b, WN1a, WN1b, MU1c)
- Data Engineer (EU1a, MU1c, WN1c, EU1a, NU1b, MU1a)
- Data scientists (SU1a, NU1a, SU1b,SU1c,WN1a, WN1b, MU1c , WN1c,WU1a,WU1b)

Participants from different studied cases explain the role of data scientists in general and discuss the roles of data scientists in their universities. For instance, a participant from SU1a stated that

"Big data tasks that include storing, analysing, and visualising big data; yes, it is the role of data scientists because they are the specialists and they can, they have a background in using the tools that are used, and they are the most people who can read the result and present the analysed data to the decision-maker in making a decision based on those data" SU1a.

Another participant mentioned that

"Based on the current stage in our university, storing, analysing and visualising it can be done by researchers and the people that working in ITC within the university EU1b".

Regarding some participants who believe that storing big data should be the responsibility of data engineering, an interviewee from EU1a stated that

"Data storage, I believe it should be the responsibility of data engineering and IT staff, not data scientists. Data analysis and visualising are the responsibilities of the data scientist EU1a".

Similarly, the participant stated that,

"If the data scientist has a team that works with the data, then storing the data should be the responsibility of the data engineer WN1a".

On the other hand, the majority of participants believe that storing, analysing, and visualising big data should be the responsibility of data scientists. Participants also provide various reasons why data scientists should be in charge of big data tasks. One participant asserted that,

"Yes, it should be the data scientist's responsibility since he/she knows the collected data and then analyses and visualises it for better decisions. The quality of stored data will make the analysis and visualisation of those data more effective, leading to better decisions WN1b".

Besides, one interviewee mentioned that,

"Data, its analysis, and presentation of the data are some of the roles of a data scientist because he is familiar with the quality of the data he has collected to serve a specific goal WN1a."

The interviewee, as a data scientist from WU1a, stated that

"It is an overlap between the task of a data scientist and the data engineer. The data engineer is often responsible for storing the data, but this does not mean that data scientists are unable to collect and analyse the data. Displaying the data is also one of the tasks of data scientists; the last level of data analysis is WU1a."

NU1b stated that

"In general, based on my experience, storing, analysing, and visualising are the tasks of the data scientist to perform them NU1b".

7.7. Organisation Culture on Big Data System Quality

In this section, the findings of research question 1 b are provided. Research question 1b explores the influence of organisational culture on big data system quality, i.e., security, privacy, and quality of big data. Organisational culture in this study is shaped by how the IT staff within Saudi selected universities and the whole organisation has a culture that accepts and adapts to big data analytics technological improvements. We will begin with the impact of organisational culture on big data security, privacy, and quality. Then the researcher will explain the interviewees' views on the impact of OC on the big data system. As the analytical focus in figure 7.1 was on the influence of OC on big data system quality, the impact of OC on big data performers, the impact of organisational culture toward big data tasks, as well as the influence of organisational culture toward decision-making, finally, the OC and its impact on improving university performance.

7.7.1. First-Order Category of Organisational Culture on Big Data System Quality BDS

The current section provides the findings relevant to research question 1C, which sought the influence of organisational culture on Big Data System Quality BDS, namely big data security, privacy, and quality. In the analysis phase, the researcher code the impact of organisational culture on system quality under four categories. These categories are organisational culture on big data security, OC on big data privacy, OC on big data quality, and organisational culture on top management staff selected universities. Table 7.7 shows the analysis of first-order categories of organisational culture on BDS.

Table 6.7. **Analysis of cross-cases First Order Categories of Organisational Culture BDS.**

Case		**First Order category of Organisational culture among Cases**				
		OCBDS	**OCS**	**OCP**	**OCQ**	**OCTM**
NU1	NU1a	√	√	√	√	
	NU1b	√	√		√	√
SU1	SU1a	√	√	√		
	SU1b	√	√			
	SU1c			√	√	√
	SU1d		√			√
WU1	WU1a	√	√	√	√	
	WU1b	√	√	√		
	WU1c					
EU1	EU1a	√	√	√	√	√
	EU1b	√	√	√	√	
MU1	MU1a	√				
	MU1b	√		√	√	
	MU1c		√			
WN1	WN1a	√	√	√	√	
	WN1b	√	√	√	√	√
	WN1c	√	√		√	
Appearance of Categories in percentage		40.08	18.88%	16.81%	11.03%	3.02%

√ – This symbol is the group of categories observed within cases. **OCBDS –** Organisation Culture On Big Data System **OCS** – Organisational Culture on Big data Security **OCP**- Organisational Culture on

Big Data Privacy **OCQ-** Organisational Culture on Big data Quality **OCTM** – Organisational Culture on Top Management

As you can see in Table 7.7, Organisational culture on Big Data System Quality is the highest observed category among the categories. This category is observed among the whole cases in this study with 40.08%. The rest of the categories and percentages associated with it will be discussed as follows

NU1: Organisational culture on big data system quality is the highest category in the case NU1. The second higher category realised in organisational culture is the impact of organisational culture on big data security. Then the influence of OC on big data privacy and the impact of OC on big data quality. Finally, the least observed category in OC is the impact of OC on big data privacy and top management staff.

SU1: the most observed form in SU1 is the influence of OC on big data security, the impact of OC on Privacy, and the quality. However, the impact of organisational culture on big data quality and top management has not been observed within SU1.

WU1: the most common category observed in WU1 is the influence of OC on the big system. Then the impact of OC on data security and privacy. The second higher observed category within the WU1 is the impact of organisational culture on big data quality. However, the impact of OC on top management staff has not been observed under the first-order category of the impact of OC on big data system quality.

EU1: in EU1, the influence of organisational culture on big data systems as the whole system is seen as the most observed category, followed by the impact of organisational culture on big data security, privacy, and quality. The effect of OC on top management staff is the least observed category in EU1.

MU1: the most observed from MU1 is the influence of OC on big system quality as the exclusive feature of the system that includes big data security, privacy, and quality. However, the influence of OC on big data security, privacy, and security, has not been observed in the case of MU1.

WN1: the influence of organisational culture on big data systems as the whole system is seen as the most observed category in WN1. The second most observed form in WN1 is the influence of OC on big data security and privacy. Third, the moderately observed form in WN1 is the effect of OC on big data quality. Finally, the least observed form in WN1 is the influence of OC on top management staff within selected Saudi Arabian universities.

In the next sections, the categories of the influence of OC on big data system quality will be discussed. Those categories and their related codes and references will be as follows, Organisational Culture on the system Quality as the whole system, Organisation Culture on big data security, organisational culture on big data privacy, and quality. Lastly, the influence of OC on top management staff will be discussed.

The influence of OC on big data system quality as the whole system functions, i.e., big data security, privacy, and quality, is the first category in table 7.6. In the current study, organisational culture is crucial since it impacts big data systems. This impact is on big data security, privacy, and quality. Besides the effect of OC on big data systems, the impact of OC on top management staff was also observed within the cases. Codes and references related to OC on big data systems realised across the studied cases are listed below.

- Accepting and adapting with BDA technology (NUIb, NU1a, WN1a, WN1b, SU1a, MU1a, MU1b EU1a, WN1b)
- Country Vision (SU1a, WN1b)
- Top management (MU1a, SU1a,EU1b,WU1b)
- OC does not impact the big data system (WU1a).

Regarding accepting and adapting to big data technologies. Participant provides various opinions about it. For instance, one participant asserted that

"The process of accepting and adopting big data technologies depends on the decision-maker in the university and also on the personality of the decision-maker, mainly on the extent of his/her awareness of the importance and analysis of big data. When the organisation's view is based on data and analysis MU1b".

Another participant stated that

"I expect that the decision-maker must support the direction of data analysis and provide the necessary facilities to support workers in analysing big data; otherwise, it will be resistance of adapting big data analytics within the university MU1a".

Besides, we asked the same participant, who is also a top management staff, about his point of view on the impact of the OC on big data system quality. The Answer was

"In my position, I am concerned about the influence of OC big data system as I am working in Deanship of IT services MU1a".

Participants from the different cases stated that accepting and adapting big data technological improvements are aligned with the country's vision

"Yes, I believe the university will accept the new technological improvements that include security, privacy, and quality of big data; it will enable it because these improvements are supported by the country vision 2030 WN1b".

Organisational culture influences top management staff who are working in Saudi Arabian universities. As one of them mentioned that

> "Any new technological improvements that top management accepted and proved it we will accept since it has been approved by top management" EU1b.

One Participant from WN1a stated that OC has no impact on the big data system. Below is the statement that he addressed

"From my point of view, it has no effect because it is related to technology more and not at the level of individuals (employees). The organisational culture does not have an effective role in the issue of technological improvements such as security."

The second category is the impact of OC on big data security. This category discusses how organisational culture can encourage information technology staff within Saudi Arabian universities at different levels to accept and adapt to big data system quality, specifically big data security. Participants from various cases included in this study provided their experiences and opinions on the influence of OC on big data security. The following are the codes and references derived from the impact of OC on big data security.

- Organisational culture on big security is vital (WN1a.WUN1b, EU1b, NU1a)
- Reduce risk (EU1a, Su1a, WN1b)
- Improve the decision-making (SU1a, WU1b).

As participants stated that organisational culture on big data security is vital.

"Security of big data is vital; in our university, one of the top management requirements is data security. In addition, our university's president focuses on technology. Therefore, this is considered as the organisational culture because it comes from top management WN1a.

Similarly, one participant mentioned that

"Since big data is a trend nowadays, securing and making this data private is vital" WU1b.

A Participant from EU1a stated that security in big data systems reduces the risk

"The answer of WHY you think organisation culture influences the security is without security you are in risk your data at risk EU1a".

The third category is related to the impact of OC on big data privacy. This category discusses how organisational culture can encourage IT, staff within Saudi Arabian universities to accept and adapt to big data system quality, specifically big data privacy. Participants from the studied cases provided their opinions on the influence of OC culture on big data privacy. Below are the interviewees' opinions related to the above category.

One interviewee mentioned that organisational culture allows the protection of personal information, and he stated that

"I believe that organisational culture will influence the privacy of big data. For example, in our university, at big data system, no one will have access to view stored data records, such as names or sensitive information UN1a".

Another participant asserted that

"For ensuring data privacy, the system hides personal information or record belong to staff and student data".

The fourth category is the influence of OC on big data quality. This category discusses how organisational culture impacts the big data system as the whole system, specifically big data quality. Organisational culture in this study shaped how IT staff within Saudi universities accept and adapt to big data technological improvements. One of those technological improvements is big data quality which can improve the system functionality since it allows data scientists to provide good quality data for better decisions. Participants from studied cases produce different opinions on their experience and views about big data quality. For instance, a participant from SU1a mentioned that

"We accept the technological improvements of big data in terms of its security and privacy and the quality SU1a".

Similarly, a Participant from WN1a stated that

"Nowadays, data is the power that distinguishes you among others; if you have big data, but it is not a good quality data serve the plans and goals of the university, then it is useless WN1a".

One participant highlighted that

"In my position, I need a good quality of analysed data to improve my technical and academic decisions WN1b".

The last category is the effect of organisational culture on top management staff. This category unfolded during qualitative data collection. This category discusses how OC can impact top management in accepting and adapting to new big data analytics technological improvements. Collected data from the interviews we coded. Below are some of the participant's views on the impact of OC within Saudi Arabian universities, including top management staff. For example, one participant from EU1a asserted that

"As I am the Vice president of Strategic planning and scientific research staff, if the stored data is not improving my decision, then why do we spend money and effort for making the system for big data EU1a".

7.8. First Order- Category of Organisational Culture on Big Data Analytics Performers BDP

This section provides the findings related to research question 1b, which sought the influence of organisational culture on big data analytics performers, specifically IT staff and data scientists. During the analysis, the researcher code the effect of organisational culture on big data performers in four categories. These categories are organisational culture on IT staff in Saudi Arabian universities, OC on data scientists, OC on the whole staff within Saudi universities, and OC on top management staff. Table 7.8 presents the analysis of cross-cases first-order categories of organisational culture on BDP.

Table 7.8. **Analysis of cross-Cases First Order Categories of Organisational Culture on BDP**

Case		**First Order category of Organisational culture among cases**			
		OCIT	**OCDAS**	**OCWS**	**OCTM**
NU1	NU1a	√	√		
	NU1b	√			
SU1	SU1a	√	√		√
	SU1b		√		
	SU1c		√		√
	SU1d	√		√	
WU1	WU1a	√	√		
	WU1b	√		√	√
	WU1c		√	√	
EU1	EU1a	√	√	√	
	EU1b	√	√	√	
MU1	MU1a	√		√	
	MU1b				
	MU1c				
WN1	WN1a	√	√		
	WN1b	√	√		
	WN1c	√	√		
Appearance of Categories in percentage		42.27%	26.8%	17.62%	14.3 %
√ - This symbols the group of categories observed within cases. **OCIT –** Organisational Culture on IT staff **OCDAS** – Organisational Culture on Data Scientists **OCWS-** Organisational Culture on whole Staff **OCTM-** Organisational Culture on Top Management Staff					

Table 7.8 shows that organisational culture on IT staff is the highest category observed among the categories. Besides, the impact of OC on IT staff was realised among the cases in this research, with 42.27%. The next section will discuss the appearance of Categories of how organisational culture impacts BDP.

NU1: in NU1, the impact of organisational culture on big data analytics performers is seen as the highest category, with a percentage of 42.27. The influence of organisational culture on data scientists consider the second higher category in NU1 with 26.8%. However, the impact of organisational culture on staff, in this case, has not been discussed; similarly, the effect of organisational culture has not been addressed in NU1.

SU1: the most realised category in case SU1 is how OC influences IT and staff within Saudi Arabian universities. The effect of OC data scientists is seen as the second higher observed category in SU1. The third observed category within SU1 is the impact that OC can carry on top management staff in this case. However, the impact of organisational culture on the whole staff that works in Saudi universities has not been observed within SU1.

WU1: the influence of OC on IT staff is the most observed category in WU1. Next is the impact of OC on the whole staff within the case. The third higher observed category within the WU1 is the impact of organisational culture on top management staff. However, the impact of OC on data scientists has not been observed in the case of WU1.

EU1: in EU1, the influence of organisational culture on IT staff is seen as the most observed category, followed by the impact of organisational culture on data scientists and the whole staff within EU1. Nevertheless, the effect of OC on top management staff has not been observed within this case.

MU1: the most observed from MU1 is the influence of OC on IT staff. The second higher observed category is the impact of OC on the whole staff that works in case MU1. Nonetheless, the influence of OC on data scientists and top management staff has not been discussed in MU1.

WN1: in WN1, the influence of organisational culture on IT staff is the higher observed category, followed by the impact of OC on data scientists. However, the influence of OC on the whole staff within the case and top management staff has not been highlighted in this case

In the next sections, categories related to the influence of OC on BDP will be discussed. Those categories and their related codes and references will be as follows, OCIT, OCDS, OCWS, and OCTM.

The impact of OC on big data performers, i.e., IT staff, is the first category in table 7.7. In the current study, organisational culture is vital since it impacts "big data performers" human factors. Codes and references related to OC on big data performers, which were realised across the studied cases, are listed below.

- Impact of OC on IT staff (NUIb, SU1d, SU1a, MU1a, EU1a, WU1c, WN1c)
- Encouraging IT staff in daily tasks (WN1a, WN1b, WN1c WU1b, EU1b, SU1d)
- Top management (SU1a, WU1a)

As for the influence of OC on IT staff, participants highlighted various views across different interviews. For instance, a participant from NUIb mentioned that

"During COVID-19, the university has implemented a system that does not allow students to cheat during online exams. This example shows the influence of organisational culture on IT staff the deal with different situations NUIb".

Likewise, another interviewee stated that

"Yes, the university administration or the decision-makers in the university, if they accepted this decision. It will greatly influence different levels within the university, from top to bottom. I mean, organisational culture will influence every level that looks at the level above; it will force it to the lower level until it includes all the levels in the university. As a result, it will change the whole university to deal with data analysis for any decisions SU1a".

Regarding the effect of OC on IT staff to perform their daily tasks, one participant mentioned that

"The answer is yes; positions, tasks force within the organisation (organisational culture) facilitate the staff's productivity since the organisational culture is known by everyone and it the main guider for the performing the tasks by IT staff EU1a".

The top management staff is found to be affected by OC. For instance, a participant from WN1a mentioned that

"Yes, accepting new technological improvements will allow the IT staff to comply with the university top management guidelines and plans and encourage the IT employees to participate in big data security and privacy WN1a".

In this paragraph, we will discuss the impact of OC on big data performers, specifically data scientists. This impact involves how organisational culture influence data scientists; Participants from different studied cases produce their opinions on the influence of OC culture on BDP. The following are the codes and references derived from the impact of OC on BDP

- Effect of organisational culture on data scientists (NU1a, SU1a, EU1a, EU1a, WN1a, WN1b)

Participants from this case agreed that OC has an impact on data scientists. For instance, one of those participants stated that

"When we talk about organisational culture on data scientists, organisational culture will allow them to make more insights of the data that they are dealing with which lead to better decisions WN1b".

The second last category is related to the influence of OC on whole employees that work in Saudi Arabian universities. This category occurred during the interviews since participants highlighted it numerous times. The following are some of the participants' views on the above category.

"Yes, the organisational culture encourages the whole staff, from top management to operational level WU1b".

Similarly, participant WU1a stated that

"It starts at the level of the Deanship, then it goes to the IT staff, of course, WU1a".

The last observed category related to OC on big data performers is the impact of OC on IT top management staff. For instance, a participant from SU1a highlighted that, "Yes, the university administration or the decision-makers in the university, if they accepted this decision. It will certainly greatly influence a different level within the university from top to bottom SU1a".

7.8. First Order- Category of Organisational Culture on Big Data Tasks BDT

In this section, we produce the findings related to research question 1b, which sought the Influence of Organisational Culture on big data tasks: storing, analysing, and visualising. During the analysis of the qualitative data, the researcher codes how organisational culture influence big data tasks in three categories. These categories are organisational culture on storing, analysing, and visualising big data. Table 7.9 presents first-order categories of organisation culture in BDT.

***Table 7.9.* Analysis of cross-Cases First Order Caetegories of BDT**

Case		First Order category of Organisational culture among cases			
		OCBDT	**OCIT**	**OCDS**	**OCDV**
NU1	NU1a	√	√		
	NU1b	√			
SU1	SU1a	√	√	√	√
	SU1b		√		
	SU1c			√	
	SU1d			√	
WU1	WU1a	√	√		
	WU1b	√		√	√
	WU1c	√	√		
EU1	EU1a	√	√	√	√
	EU1b	√			
MU1	MU1a	√			√
	MU1b		√		
	MU1c	√			
	MU1d		√	√	
WN1	WN1a	√			

	WN1b	√			
	WN1c		√	√	
Appearance of Categories in percentage		37. 71%	10.73 %	8.54%	33.65%
√ - This symbol is the group of categories observed within cases. **OCBDT –** Organisation Culture On Big Data Tasks (Storing, analysing, visualising) **OCIT** – Organisational Culture on IT Staff **OCDAS-** Organisational Culture on Data Scientists **OCDV-** Organisational Culture on Data Visualisation					

Table 7.9. Presented data shows that organisational culture on Big Data Tasks BDT was the highest among the categories, with 37. 71%. The second higher category is the influence of organisational culture on data visualisation, with 33.65%. The second last category is the impact of OC on IT staff responsible for storing big data 10.73%. Finally, the least realised category is the influence of OC on data scientists, which are responsible for big data analysis, with 8.54%. The next section will discuss the appearance of categories of how organisational culture impacted BDT in each studied case in our study.

NU1: the impact of organisational culture on big data tasks that include storing, analysing, and visualising is seen as the highest observed category in NU1 with a percentage of 47.71%. The influence of OC on IT staff responsible for storing big data is seen as the second highest category in NU1, with 10.73%. However, the impact of organisational culture on data scientists and data visualisation has not been addressed in NU1.

SU1: the most realised category in case SU1 is how OC influences big data tasks, namely storing, analysing, and visualising. The effect of OC on data visualisation is the second observed category in SU1. The third realised category within SU1 is OCs impact on IT staff. Finally, the last category is the influence of OC on data scientists.

WU1: within the studied case, WU1, the data shows that OC influences big data tasks the most observed among the cases. In comparison, the second observed category within the same case is the influence of OC on IT staff which are mainly responsible for data storage. However, the influence of OC on data scientists and data visualisation has not been observed in WU1a.

EU1: in EU1, the influence of organisational culture on big data tasks is seen as the most observed category followed by organisational culture's impact on data scientists, IT staff, and data scientists. Nevertheless, the effect of OC on data visualisation has not been observed within this case.

MU1: data shows organisational culture impact on the BDT is the higher observed category in MU1. The second higher observed category is the effect of OC on big data visualisation. Nonetheless, the influence of OC on IT staff for big data storage, and data scientists, have not been discussed in MU1.

WN1: in WN1, the effect of organisational culture on big data tasks is observed only once. However, the impact of OC on IT staff, data scientists, and data visualisation have not been observed within WN1.

Categories related to the influence of OC on BDT will be discussed in this section. Those categories and their related codes and references will be as follows, the impact of organisational culture on big data tasks, the influence of organisational culture on IT staff, which is responsible for big data storage, the effect of organisational culture on data scientists, and lastly how organisational culture impacts the visualisation of analysed data.

In this paragraph, we will discuss the first category related to the influence of organisational culture on BDT, i.e., acquiring, analysing, and visualising analysed data. As shown in table 7.9, the effect of OC on big data tasks has been observed within the whole case in our study as participants provide different opinions on such influence. Thus, the following codes and related references among the cases were derived.

- OC supports BDT (WN1a, SU1b,MU1a, EU1b, EU1a, WU1b, NU1a, MU1d)
- OC will improve the current technology (NU1b, WN1c, MU1d)

Collected data related to the impact of organisational culture on big data tasks revealed that most participants from the cases stated that organisational culture impacts big data tasks. For example, participants pointed out that OC encourages universities to store, analyse and visualise big data to make better decisions.

"Yes, organisational culture is vital because it allows the storage, analysis, and visualisation of the data within our systems; therefore, we can take advantage of those data in our university EU1a".

Another participant indicated that

"In my view as the decision-maker, yes, organisational culture represented as the enabler of storing, analysing, and visualising data from various resources will improve the decision making. It will allow the data scientists or engineers to store, analyse, and visualise the data from different places for better decisions. This applies to the organisations in the early stage of implementing BDA for improving top management decisions UWN1b".

On the other hand, the interviewee stated a new impact that OC can carry out on big data tasks. Participant stated that

"Since it encourages the top management to implement the recent technology that enables the university to capture, analyse, visualise big the data NU1b".

The second category listed in Tables 7.8 is the impact of OC on big data tasks. The codes and references associated with this category show that organisational culture also plays a vital role in IT staff participating in big data storage. The codes and references for the impact of this category are listed below.

- OC impacts IT staff (SU1a,NU1a,WU1a,EU1a, WN1c, MU1b ,MU1d)

"In my opinion, organisational culture assists IT staff to store, analyse, and visualise big data for making decisions SU1a".

Similarly, the interviewee mentioned that,

"I see the organisational culture plays a role on the technical and human level, but I think the impact will be greater on the human level. I mean human resources. You can buy technology, but if you do not have a staff that works with technology, it will not" NU1a.

Regarding the impact of OC on data scientists, participants stated that,

"Organisational culture will allow the data scientists or data engineers to store, analyse, and visualise the data from different places for better decisions WN1b".

The last category associated with the impact of OC on big data tasks is how organisational culture enables the visualisation of analysed data. For instance, the participant stated that

"Many applications are now possible that support decision-making to rely on information that depends on presentation technology MU1a".

7.9. First Order- Category of Organisational Culture on Improving Decision-Making DES

In this section, we present the results of research question 1c, which examined the influence of organisational culture influences the decisions of top management. The impact of organisational culture on improving decision-making was divided into four categories while examining the qualitative data. These categories are organisational culture on improving decision-making, organisational culture in general, organisational culture that forms the policies, and organisational culture's impact on data visualisation. First-order categories of organisational culture on improving decision-making are shown in Table 7.10.

Table 7.10 **Analysis of cross-Cases First Order Categories of organisational culture on DES**

Case		**First Order category of Organisational culture among cases**			
		OCDES	**OC**	**OCPs**	**OCDV**
NU1	NU1a	√			√
	NU1b	√			
SU1	SU1a	√		√	
	SU1b		√	√	
	SU1c		√	√	
	SU1d		√		
WU1	WU1a	√			√
	WU1b	√		√	√
	WU1c	√	√		
EU1	EU1a	√	√		√
	EU1b	√		√	√
MU1	MU1a	√	√		
	MU1b		√		
	MU1c	√			
	MU1d		√	√	

WN1	WN1a	√		√	√
	WN1b	√		√	√
	WN1c		√	√	√
The appearance of Categories in percentage		65.2%	18.5 %	6.3%	10%
√ - This symbol is the group of categories observed within cases. **OCDES –** Organisation Culture On Improving Decision-Making **OC**– Organisational Culture in general- Organisational Culture Policies **OCDV-** Organisational Culture on Data Visualisation					

Table 7.10 demonstrate that the influence of organisation culture on enhancing the decision-making by top management had the highest percentage, with 65.2%. However, the impact of organisational culture on the whole firm is the second highest category, with 18.5%. Then the effect of organisational culture on data visualisation with 10%. Lastly, the influence of organisational culture on the policies within the firm is the second last, with 6.3%. The next section will discuss the appearance of categories on the impact of organisational culture on enhancing top management's decision-making.

NU1: the influence of organisational culture on improving decision making is seen as the highest category among the cases. Then, how does organisation culture impact the whole organisation viewed as the second highest category within NU1. The influence of OC on data visualisation is seen as the third category. However, organisational culture's impact on forming the firms' policies is seen as the last category in NU1.

SU1: the highest category observed in this case is organisational culture's influence on forming the firm's policies. The second observed category within SU1 is the impact of organisational culture toward making decisions. However, the effect of organisational culture on data visualisation was not observed in SU1.

WU1: in this case, the influence of organisational culture on improving decision-making is seen as the first category. Then, the impact of organisational culture on data visualisation is seen as the second-highest observed category in WU1. Then organisational culture's effect on forming the firms' policies is seen as the third observed category. However, the influence of organisational culture on the whole organisation was not observed in WU1.

EU1: the influence of organisational culture on improving decision-making is seen as the most observed category in EU1, followed by organisational culture's impact on data visualisation. Then the impact of organisational culture on the whole organisation is seen as the third highest category in EU1. Lastly, the effect of organisation culture on forming the policies within the firm is the least observed category in EU1.

MU1: data shows that the impact of organisational culture on improving decision-making is the higher observed category in MU1. The second highest observed category is organisational culture's effect on forming the firm's policies. Nonetheless, the influence of OC on IT staff for big data storage, and data scientists, have not been discussed in MU1.

WN1: the data indicate that the highest category in WN1 is the influence of organisational culture on forming the policies within the firm. The second highest category in WN1 is the influence of organisational culture on improving data visualisation. The third observed category in WN1 is the impact of organisational culture on improving decision-making. Finally, the last observed category is the influence of organisational culture on the whole organisation.

In this section, the significance of organisational culture in improving the decision-making will be discussed, followed by the importance of organisational culture on data visualisation, and then the impact of organisational culture on forming the policies within the firm.

First, we will highlight participants' opinions on the influence of organisational culture on improving decision making.

For instance, participant MU1 stated that

"Currently, the university is jumping to a big change in terms of academics and technologies; based on that. I agree that, yes, organisational change will improve the decision-making process. For example, shifting from making a decision based on experience to relying on BDA MU1".

Similarly,

"Organisational process (culture) transfers periodic maintenance reports. These periodic maintenance reports are on the existing systems at the university. If they are collected electronically, there is an electronic analysis process; we have obtained valuable results that return to us to facilitate decision-making. Therefore, the organisational process is necessary, not a luxury WN1b."

Considering the influence of organisational culture on data visualisation, one interviewee stated that,

"Data collection and presentation in a simple way to decision-makers. It will contribute to a strategic change and new strategies for the organisation. Data integration with management is a prerequisite for the success of the organisation. Many applications can now support decision-making based on information that depends on presentation technology. Thus, it will assist decision-makers in making the best decisions based on effective data visualisation. MU1"

Likewise, the participant from WN1b stated that

"Many topics are included in modern technical systems that contribute to decision-making, security systems, and quality follow-up systems. I mean, we have a group of theses that I reviewed for a while. They were unified digital platforms in which the university director could enter the most accurate details that he had in the university, including the transfer, for example, of a membership card. The teaching staff, so that if, for example, love came to assigning a certain person to a specific assignment, the matter would not be based on WN1b."

Lastly, one participant indicates the importance of organisational culture in forming the firm's policies. He stated that

"The culture of our organisation must be consistent with the policies related to the data, and to ensure that the decision is made is encouraged by OC that guides the decision maker to make their decision based on big data analytics. Thus, organisational culture is critical in improving decision-making using new technologies such as BDA. So yes totally agree with this statement. WN1a"

In the next section, the impact of organisational culture on improving overall university performance will be presented.

7.10. First Order-Category of Organisational Culture on Improving University Performance OP

In this section, we present the results of research question 1c, which sought the impact of organisational culture on improving university performance will be discussed in this section. This influence includes improving the performance of the university in generating business value for the university and creating academic achievements. Beside the impact of organisational culture on creating business values and academic outcomes, the influence of organisational culture on information technology was also observed among the cases. First-order categories are shown in table 7.11.

***Table 7.11.* Analysis of cross-Cases First Order Categories of organisational culture on OP**

Case		First Order category of organisational culture among cases			
		OCOP	**OCBV**	**OCA**	**OCIT**
NU1	NU1a	√	√	√	√
	NU1b		√		
SU1	SU1a		√	√	
	SU1b	√			√
	SU1c		√		√
	SU1d	√	√	√	
WU1	WU1a	√			√
	WU1b	√		√	√
	WU1c		√		
EU1	EU1a	√	√		√
	EU1b	√	√	√	√
MU1	MU1a	√			
	MU1b		√		
	MU1c	√			
	MU1d		√	√	
WN1	WN1a	√	√	√	√
	WN1b	√	√	√	
	WN1c		√	√	

The appearance of Categories in percentage	44.7%	14.4 %	32.5%	8.2%
√ - This symbol is the group of categories observed within cases. **OCOP –** Organisation Culture On Improving University Performance OCBV– Organisational Culture in creating Business Values- Organisational Culture in creating Academic Outcomes **OCIT-** Organisation Culture on Information Technology.				

Table 7.11 shows that, with a percentage of 44.7%, organisational culture has the greatest impact on improving university performance. However, at 32.5%, the second highest category is the effect of organisational culture in creating academic outcomes—next, the impact of organisational culture on creating business values with 14.4%. Finally, with 8.2% of the vote, organisational culture impacts information technologies within the university. In this section, we will discuss the occurrence of the categories related to the influence of organisational culture on improving university performance.

NU1: The highest category among the instances is the impact of organisational culture on creating business values. As the second higher category in NU1, how does organisational culture affect improving university performance? The third is the impact of organisational culture in creating academic outcomes. The last observed category is the impact of organisational culture on information technology within the firm.

SU1: the highest category observed in this case is organisational culture's influence on forming the firm's policies. The second observed category within SU1 is the impact of organisational culture toward enhancing top management decisions. However, the effect of organisational culture on data visualisation was not observed in SU1.

WU1: the influence of organisational culture in creating business values for the university is seen as the highest observed category in WU1. Then the impact of organisational culture on information technologies within the university. The third observed category in WU1 is the influence of organisational culture on improving university performance. Finally, the last observed category in WU1 is how organisational culture creates academic outcomes.

EU1: organisational culture and its impact on improving university performance is seen as the first observed category in EU1. Second is the impact of organisational culture on information technology within the university. The third is the impact of organisational culture on creating business values, followed by organisational culture on creating academic outcomes.

MU1: The significance of organisational culture in improving university performance is seen as the highest category in MU1, followed by the influence of organisational culture in creating business values for the university. However, the impact of organisational culture in creating academic outcomes and information technologies has not been observed in MU1.

WN1: in this case study, organisational culture and its impact on improving university performance is the highest observed category, followed by the influence of organisational culture in creating business values. Then, the impact of organisational culture in creating academic outcomes. Finally, the last observed category in WN1 is how organisational culture affects information technologies within the university.

In this section, we will present participants' opinions regarding the influence of organisational culture on improving university performance, creating business values and academic outcomes, and the impact of organisational culture on information technology within the university.
Regarding the significance of organisational culture in improving university performance, participants from

"In this scenario, improving organisation performance must go through some sequences. If we have to improve, for example, university performance, numerous factors have to be considered; one such is OC, which encourages everyone within our university we have this vision to achieve. Then you measure how many objectives have been achieved WN1a. "

Also, an interviewee from MU1a stated that

"An organisational culture that encourages and assists us will certainly improve our university performance. For example, allowing top management to adapt and accept the new BDA technologies will make you unique among other universities. The university's ranking will also improve because you allow new technologies to improve the current performance."

Similarly,

"NU1a addressed that in the past, there was no system for internal messaging system among the employees. Therefore, the employee has to write the request to the upper management to prove it then he could request to top management. Later, we built a system allowing employees to make requests through the system. This improvement assists the top management in focusing on specific objectives and making the system perform such tasks. As a result, it improves the performance of top management to concentrate on bigger objectives NU1a."

Regarding the impact of organisational culture in creating business values and academic outcomes, participants stated that

"In my opinion, it will improve the university performance mostly in the academic field; if your academic part improves, it will improve the overall university performance MU1a."

WN1a also indicated that

"Yes, of course, the use of big data analysis will improve the organisation performance; it will improve transparency. Yes, all universities aim to improve academic (educational) performance. Analysing big data will improve the university's academic performance. Improving technology performance will also definitely improve academic performance.

BDA will also help bring in high-quality faculty members, improving academic performance. An important point is also big data analysis helps open new specialisations at the university level to keep it with the market's need for graduates of certain specialities"WN1a.

WN1b also stated that

"In my opinion, it will improve academic decisions. For instance, if we would like to open a new major, we will be relying on the data being analysed; if we want to merge two colleges will be making a decision based on the analysed data"WN1b.

The next section discusses another important factor of this study: the significance of big data system quality includes big data security, privacy, and quality.

7.11. Big Data System Quality (BDS) on Improving Decision Making (DES)

The findings of research question RQ2 are provided in this section. Research question two sought to explore the influence of BDS i.e., security, privacy, and quality, on enhancing decision making. BDS in this study is shaped by how security, privacy, and the quality of analysed data contribute to enhancing top management decisions. Big data security in this study means that decision-makers are making their decisions relying on the system that secured the data and limiting the access to those data to be accessed by decision-makers only. Privacy in the big data system means protecting personal information such as medical reports and any information associated with people. Big data quality means that the system allows data scientists to store a good quality of analysed data and make it available for decision-makers to make the best decisions. Improving this study's decision-making includes enhancing financial, strategic, and academic decisions. We will begin with the first-order category of big data system quality, then cross-case analysis of data, followed by participants' opinions and experiences about the influence of the quality of big data systems on decision making.

7.11.1 First Order Category of Big Data System Quality BDS Improving Decision Making (DES)

The current section provides the findings related to research question 2a, which explores the influence of big data system quality, namely big data security, privacy, and quality, on improving decisions by executives. In the analysis phase, we code the impact of big data security, privacy, and quality on enhancing decision-making in three categories. These categories are security of big data, privacy, and quality. Table 7.10 shows the analysis of cross-cases related to BDS on improving the decision-making by top management.

Table 7.10. **Analysis of cross-Cases First Order Categories of Big Data System Quality BDS.**

Case		**First Order category of Big Data System Quality among the cases**		
		SEC	**PRI**	**QUA**
NU1	NU1a	√	√	√
	NU1b		√	
SU1	SU1a	√	√	
	SU1b		√	
	SU1c	√	√	
	SU1d			√
WU1	WU1a	√	√	
	WU1b			√
	WU1c	√		
EU1	EU1a		√	√
	EU1b	√	√	√
MU1	MU1a	√	√	√
	MU1b			
	MU1c			
WN1	WN1a	√		√
	WN1b	√		√
	WN1c		√	
Appearance of Categories in percentage		29.82%	33.64%	36.54%
√ - This symbols the group of categories observed within cases. **SEC** – Security of BD **PRI** – Privacy of BD **QUA-** Big Data Quality				

Table 7.10 above shows the appearance of categories in percentage among the cases in our study. The table also shows that the highest category among the cases is big data quality and its role in enhancing decisions—for example, executives. The second highest category is the privacy of BDS and the significance of the system in making big data privacy and protecting any personal information of the collected data (standard policy). Finally, the third highest category in the above table is big data security that allows the

decision-makers to make decisions based on a solid system that strictly controls the access of stored data. In the next sections, we will address the appearance of categories of each case related to the system of big data.

NU1: big data system quality, specifically big data privacy, is the highest category in the table above. Big data quality is seen as the second-highest observed category in NU1.

Big data security in NU1 is the least observed category in this case.

SU1: the most realised category in case SU1 is the impact of big data security on improving Saudi Arabian universities' decision-making. Big data privacy is considered the second-highest category in SU1. Big data quality, however, has not been observed in SU1.

WU1: within the studied case, WU1 data shows that big data security is the most observed in WU1. The second realised category is big data quality. However, big data security has not been observed in this case.

EU1: in EU1, the privacy of big data quality is seen as the most observed category, followed by the big data quality toward improving decision making. The least realised category is the security of big data.

MU1: data shows that big data quality is the highest observed category in MU1. Big data privacy's effect on top management's decision-making is the second highest observed category. Security in MU1 is seen as the least realised category.

WN1: in WN1, big data quality and its effect on enhancing the decision-making is the highest category. The second highest category in WN1 is big data security. However, big data privacy has not been observed in WN1.

This section will discuss the categories associated with big data system quality: big data security, privacy, and quality. Those categories and their related codes and references will be SEC, PRI, and QUA.

We will begin the security of big data, which involves big data system quality. As participants stated, the security of the big data system increases the effectiveness of the decisions being made since the system allows its users, "decision-makers" to make their decisions based on secured data accessible by anyone. These codes and references were derived from the interviews when we asked them about the importance of the security of big data and its role in improving decision-making in Saudi Arabian universities.

- Data sensitivity (MU1a, WN1b, WU1a, NU1a)
- Significance of SEC (WN1b, WN1a, MU1a, MU1a, EU1b, SU1a, SU1c)

Regarding big data security, some participants indicated that the level of the security of BD depends on the sensitivity of the data. For instance, the interviewee stated that,

"Data security depends on the nature of the data being collected. Meaning that the more the data is important, the more restricting the access to those data" MU1a.

Similarly, another participant mentioned that

"Sensitive data cannot be accessed by top management staff expecting the decision-makers. All of these activities will improve big data security" NU1a.

Besides the security of big data, the privacy of big data is the second factor in big data system quality. Privacy in this study focuses on the standard policy that Saudi Arabian universities should apply when storing data related to people or sensitive information that can identify people. Participants yield different views on big data privacy. Thus, these codes and references have been copied from the collected data.

- Big data privacy protects personal identity (MU1a ,EU1b, WN1b, WU1b, WU1b ,NU1b)
- Significance related to BD privacy (UN1a, UN1b, WN1b, EU1a, SU1b, MU1a, EU1b, SU1a)

Participants highlighted the role of big data privacy in protecting personal identity. For example, interviewees stated that

"Privacy has the same significance as data security, allowing top managers to make decisions based on private data. For example, data privacy allows the executives to make decisions without considering personal information that can affect the decisions, i.e., personal relations or interests MU1a".

Likewise, another participant also mentions how big data privacy contributes to improving executives' decision-making. The participant stated that

"The system allows the data scientist to stamp any sensitive records that can identify the persons, so the decision-makers can make their decisions without knowing any names written in the reports WU1a".

The same participant stated that

"Big data systems also generate the time assigned to the decision-makers that can view the records"WU1a.

Participants also mentioned the significance of big data privacy and how it can enhance top managers' decisions. For instance, a participant stated

"Privacy in data analysis works on improving decision-making, starting from collecting sufficient data in preparation for extracting useful information and thus making the right decision" WN1b.

The third factor involved in big data system quality is the quality of big data and its role in enhancing the decisions of executives.

- The effectiveness of data on decision making (WU1b, NU1b, SU1a, MU1a)
- Importance of data quality (UN1a, UN1b, WN1b, EU1a, MU1a, EU1b, SU1a, SU1d)

The effectiveness of data quality plays an important role in the quality of decisions being made. As participants mentioned during the interviews. For instance, a participant from

"This is nature, and good analysis leads to effective decisions. Today data is everything. Now the government is analysing big data for gaining good decisions WU1b".

Correspondingly, one participant asserted that

"When it comes to the quality, the higher the data quality, the better decision you can make" NU1a."

Equally important is that various participants highlighted the importance related of the quality of analysed data in improving decision making. For instance, one interviewee stated that.

"Let us say about the system in general, yes, one of the most important decision-making factors is the speed of decision-making at present. If there are no systems that allow saving the analysed data of high quality, the presence of systems of this type will certainly lead to improved decisions. Decision-making at present depends on data quality, for example, returning to the in-person study, and some other decisions, such as the distribution of faculty members, depending on data collected and analysed to make the decision. This confirms that the quality of the analysed data has a major role in the issue of decision-making at all levels in the university" WN1a. In the next section, we will discuss the findings of how BDT on DES

7.12. Big Data Tasks (BDT) on Improving Decision Making (DES)

This section discusses results associated with research question 2b, which explores how big data tasks enhance top management decisions. BDT in this study is formed as how to store big data from various reliable sources, analyse data that comes from various resources, and visualise those analysed data that can improve executives' decisions. The discussion of the first-order category related to big data tasks will be in the next section, followed by participants' opinions and experiences about the effect of big data tasks on improving decision making.

7.12.1 First Order-Category of Big Data Tasks (BDT) on Improving Decision Making (DES)

This section presents the results associated with research question 2, which investigates the impact of big tasks: storing big data, analysing stored data, and visualising those analysed data. In the analysis phase, we code the effect of those tasks in four categories. These categories are general big data tasks that involve the tasks mentioned above: storing big data, analysing big data, and visualising analysed data. Table 7.12 presents first-order categories of BDT for improving decision-making by executives.

Table 7.12. Analysis of cross-cases First Order Caetegories of BDT

Case		First Order catgry of BDT among the cases			
		BDT	**STO**	**ANA**	**VIS**
NU1	NU1a	√	√	√	√
	NU1b	√	√		√
SU1	SU1a	√	√	√	
	SU1b		√		
	SU1c			√	
	SU1d		√		√
WU1	WU1a	√	√	√	
	WU1b	√			√
	WU1c				
EU1	EU1a	√	√	√	
	EU1b	√	√		
MU1	MU1a	√	√	√	√
	MU1b	√			√
	MU1c		√		
WN1	WN1a	√	√		√
	WN1b	√	√	√	√
		√			√
Appearance of Categories in percentage		56.57%	19.03%	13.45%	10.95%
√ – This symbols the group of categories observed within cases. **BDT –** Big Data Tasks **STO** – Storing Big Data **ANA**- Analysing Big Data **VIS** – Visualising Big Data					

Table 7.12 demonstrates the appearance of categories in percentage among the cases involved in this study. Based on the data in the above table, big data tasks as the whole process, such as storing, analysing, and visualising analysed data, is the highest category among the cases with 56.57%. The second highest observed category in the table above is storing big data, with 19.03%. The third realised category in the above table is analysed for those stored big data with 13.45%. Finally, the least observed category is the visualisation of analysed data for making decisions by top managers in Saudi Arabian universities, with 10.95%. Next section, we will discuss the appearance of each case in detail.

NU1: big data tasks that include storing, analysing, and visualising are considered the highest observed category in NU1, with 56.57%. Then storing big data is observed as the second highest category in NU1 with 19.03%%. Big data analysis is the third observed category in NU1. Least realised category in NU1 is the visualisation of analysed data.

SU1: the most realised category in case SU1 is big data tasks as the whole process, storing big data, and analysing big data are the highest observed categories, respectively.

Nevertheless, visualising analysed data has not been observed in SU1.

WU1: within the studied case, WU1, the data shows that big data tasks are the highest category. The second observed category within the same case is storing big data, and the third is analysing big data. Therefore, big data visualisation is the least observed category in WU1.

EU1: in EU1, big data tasks are seen as the most observed category followed by storing big data. The third category in case EU1 is analysing big data. Nevertheless, big data visualisation has not been realised in EU1.

MU1: data shows that the big data tasks are the higher observed category in MU1. The second highest observed category is big storage—then big data analysis followed by visualisation of analysed data.

WN1: in WN1, the observed category is big data tasks. The second one is big data storage. The third is the visualisation of analysed data. Finally, the fourth realised category in WN1 is the analysis of stored data. The next section will discuss tasks with codes and references related to big data.

Big data tasks as the whole process are seen as the highest category within cases. Participants from the whole case have mentioned the significance of BDT in enhancing the decision-making. For instance, participants stated that,

"From my point of view, the data must be presented. Data analysis. Data collection and presentation in a simple way to decision-makers. It will contribute to a strategic change and new strategies rooms for the organisation" MU1a.

Besides, WNU1a pointed out

"100% the different data sources will give the decision-maker more freedom in decision-making, in the current stage, the data from sources other than the university sources led to some decisions being made" WNU1a.

Participants from several cases mentioned that big data should come from various resources for storing big data. Thus, this process enhances the decisions made by executives in Saudi higher institutions. The following codes are derived from collected data related to big data storage.

- power of data for decision-making (EU1b, WU1b, WN1b, SU1a, MU1a)
- Data storage and its resources (UN1b, WN1b, EU1a, MU1a, EU1b, SU1a)

A participant from EU1 mentioned that

"Yes, it is not optional. It is a must because you cannot do any step further without solid data; every college within the university should do these steps to help them in their strategic plan and KPI for making the decision based on these data, and we should not make any decision without the support of the data, evidence from the data EU1a".

Additionally, the interviewee points out

"Outsourcing of data and analysis will lead to better decision-making. For instance, the data from the ministry of health shows the people who have taken the COVID vaccine. This data enabled the top management to decide the study mood, either to be on campus or online WNU1a."

Regarding big data sources, participant highlighted that

"Yes, there must be multiple channels of data. This starts with your employees. What do you have? As well as social media platforms, for example, social media allows organisations to store effective data and the useful place of interaction with organisations, stakeholders, and customers WNU1b".

Participants from studied cases also highlighted the importance of big data analysis. For instance, one participant stated that

"The variety of this data will allow the managers to make the best decisions because the analysed data comes from different sources WU 1a".

"Yes, I support that the data comes from various resources for data analysis. For example, data from the ministry of education regarding new regulations is very effective for us to make our decisions based on such data" SU1a.

Participants mentioned visualisation of analysed data. For example, MU1a stated that

"Naturally, since we need to store good data for analysis and then visualise it to make the best decisions. Also, data sources have to be reliable to make the best analysis then best decisions" NU1b.

7.13. Improving Decision Making (DES) on Improving University's Performance OP

This section addresses the impact of improving decision-making toward improving the university's performance. Decision-making enhancements in this study are shaped into three categories. The first is improving financial decisions. The second is enhancing strategic decisions. Lastly is improving academic decisions. Those decisions could improve the university's performance in creating business values and academic outcomes. The first-order category associated with DES will be discussed in the next section, followed by participants' opinions and experiences about the effect of such improvements on university performance.

7.13.1. First Order-Category of DES on Enhancing University's performance

This section presents the findings related to research question 3, which attempts to explore the impact of improving top management's decision on enhancing the university's performance. During the analysis phase, we code categories associated with the impact of improving DES on OP in four categories. The first is improving the whole, including financial, strategic, and academic decisions. The second is improving financial decisions. Third, improving strategic decisions. Fourth is improving academic decisions Table 7-13 illustrates first-order categories of improving executives' decision-making on university performance.

Table 7.13. **Analysis of cross-cases First Order Caetegories of DES**

Case		**First Order categry of improving decision making among the cases**			
		DES	**FND**	**STD**	**ACD**
NU1	NU1a	√	√	√	√
	NU1b	√			√
SU1	SU1a	√		√	√
	SU1b		√	√	
	SU1c		√		√
	SU1d	√		√	
WU1	WU1a	√		√	
	WU1b		√		√
			√	√	
EU1	EU1a	√	√		√
	EU1b	√		√	
MU1	MU1a	√	√		√
	MU1b			√	√
	MU1c	√		√	
WN1	WN1a		√		√
	WN1b	√		√	
	WN1c		√	√	
Appearance of Categories in percentage		56.91%	14.99%	9.12%	17.98%

√ - This symbols the group of categories observed within cases. **DES** – Improving Decision Making **FND** – Financial Decisions **STD-** Strategic Decisions **ACD** – Academic Decisions

Table 7.13 shows the appearance of categories in percentage among the cases included in this study. Improving decision-making in all areas, including strategic, financial, and academic decisions, is considered the highest category among the cases. The second highest category in the above table is improving academic decisions, with 17.98%. Enhancing financial decision-making is the third highest category, with 14.99%. The least observed category is the improving strategic decisions by top managers in Saudi Arabian universities, with 9.12%. Next section, we will discuss the appearance of each case in detail.

NU1: improving decision-making that includes financial, strategic, and academic decision-making is seen as the highest observed category in NU1 with a percentage of 56.91%.The second highest category in NU1 is that improving academic decisions will improve university performance with 17.98%%. The third observed category in NU1 is that improving financial decisions will allow the university to enhance the university's performance. Finally, the last observed category is improving strategic decision-making and its impact on higher education firms in Saudi Arabia.

SU1: the most observed category in case SU1 is improving decision-making, including strategic and academic decisions. Second, improving academic decisions will improve the university's performance. Third, improving strategic decisions is seen as the third realised category in SU1. Nevertheless, financial decisions and their roles in improving a university's performance have not been observed in SU1.

WU1: The data shows that improving decision-making DES is the highest category in this case. The second observed category within the same case is improving academic decisions and their impact on enhancing university performance. The third category is improving strategic decisions toward university performance.

EU1: in EU1, DES is seen as the most observed category, followed by improving financial decision making and its influence on firm performance. Nevertheless, strategic and academic decisions have not been realised in EU1.

MU1: data shows that the DES is the higher observed category in MU1. The second higher observed category is improving academic decisions toward university performance. Then improving financial decisions is seen as the third observed category in MU1. However, strategic decisions have not been observed in MU1.

WN1: in WN1, the most observed category is improving decision-making, which includes financial, strategic, and academic decisions. The second one is academic decisions and their impact on a university's performance. The third is financial decisions. However, strategic decisions have not been observed in WN1.

After discussing the appearance of categories in percentage, we would like to provide the participant's points of view and their experiences regarding the abovementioned categories in the next sections.

The first category is improving decision-making, which involves improving financial, strategic, and academic decisions. For instance, Participants mentioned that

"Analysing big data will enhance deciding all levels, especially academically and commercially, as I mentioned previously" WNU1.

Another interviewee stated that

"Any decisions concerning top management will improve the overall university performance WU1b".

Regarding the participants who believe that improving finances will enhance university performance. As an example of such belief, one participant pointed out,

"I believe BDA analytics will mostly enhance the effectiveness of academic decisions. As one of the academic areas in which BDA will assist, it will enable us to determine if we need to open new majors in our university NU1a."

Similarly, another participant highlighted that

"In my opinion, it will improve the university performance mostly in the academic field; if your academic part improves, it will improve the overall university performance" SU1a.

Some participants believe that enhancing strategic decisions will improve the university's performance. As an instance, one participant mentioned that,

"Improving strategic decisions will enhance performance, allowing me to make a strategic plan for IT developments in the next five years. For example, what are the new tools needed for the new technology" WU1b.

More importantly, the majority of the participants believe that improving academic decisions by top management will improve university performance since it is an educational institution, and the main objective of such organisations is to enhance their performance associated with academic outcomes. For example, one participant stated that,

"Our university is considered an educational institution; enhancing our academic decision lets our university improve its position by focusing more on improving the current performance; how are we performing this year? How about next year? It is a kind of guide to achieving our goals and plans". MU1a

Another participant also mentioned BDA's importance in enhancing academic decision-making, which enhanced university performance. She stated that

"In my opinion, it will improve academic decisions. For example, if we would like to open a new major, we will rely on the data being analysed; if we want to merge two colleges, we will make a decision based on the analysed data WN1b."

7.14. Big Data Performers BDP on Improving Decision-Making DES

This section presents the significance of Big Data Performers, such as IT staff and data scientists, in improving the decision of executives. These improvements include financial, strategic and improving academic decisions. The first-order category associated with BDP will be discussed in the next section, followed by participants' opinions and experiences about the roles of social-subsystem, i.e., BDP, in improving the decisions of top management staff.

7.14.1 First Order-Category of BDP on Improving Decision-Making DES

This section presents the results related to how big data performers impact decision-making. During the analysis phase, we code forms connected with the roles of BDP in improving decision-making in four categories. First is the effect of data scientists toward decision-making. Then the effect of IT Staff on DES, OC on big data performers, and the influence of technology on assisting BDP decisions. Finally, table 7.14 demonstrates first-order categories of improving executives' decision-making on university performance.

***Table 7.14*. Analysis of cross-cases First Order Categories of BDP**

Case		**First Order category of improving decision making among the cases**			
		DASDES	**ITSDES**	**OCDES**	**ITDES**
NU1	NU1a			√	√
	NU1b				√
SU1	SU1a	√			√
	SU1b			√	
	SU1c	√	√		√
	SU1d	√		√	
WU1	WU1a	√		√	
	WU1b		√		√
	WU1c			√	
EU1	EU1a	√	√		√
	EU1b	√			
MU1	MU1a	√			
	MU1b			√	√
	MU1c	√	√	√	
WN1	WN1a				√

	WN1b		√		
	WN1c		√	√	
Appearance of Categories in percentage		34.9%	17.2%	29%	18.9%
√ – This symbols the group of categories observed within cases. **DES** – Improving Decision Making **DASDES** – Data Scientists on Decision-Making **ITSDES** –Information Technology Staff on Decision-Making- **OCDES** – Organisational Culture on Decision-Making **ITDES – Information Technologies on Decision-Making**					

Table 7.14 shows the appearance of categories among the cases included in this research. The impact of big data performers, specifically data scientists, are seen as the highest category among the cases. The second highest category in the above table is the influence of organisational culture on improving decision-making. Then, the importance of information technology infrastructure is the second last. Finally, the least observed category is the impact of IT staff on improving decision-making. Next section, we will discuss the appearance of each case in detail.

NU1: the effect of organisational culture on enhancing the decision-making by top management is seen as the highest observed category in NU1, with a percentage of 29%.The second highest category in NU1 is how information technologies such as BDS impact decision-making, with 18.9%. However, the importance of big data performance, i.e., IT staff and data scientists, were not observed in NU1

SU1: the most observed category in SU1 is the importance of social-subsystem factors "BDP", particularly the influence of data scientists on improving decision-making, with 34.9%. Then, the importance of organisational culture is the second highest observed category in SU1, with 29%. Third, how big data technologies influence decision making with 18.9%. Last is the impact of IT staff on improving decision-making, with 17.2%.

WU1: The data shows that data scientists and their roles in improving decision-making are the highest observed category, with 34.9%. The second observed category within WU1 is the role of OC in improving the decisions of executives, with 29%. The third category is information technologies, i.e., BDS on improving the decisions of top managers in Saudi universities 18.9%. Finally, the last observed category is the role of information technology staff on enhancing the decisions making by top management with 17.2%.

EU1: the impact of data scientists on improving decisions of executives. is seen as the most observed category, with 34.9%, followed by information technologies such as BDS and its influence on decision-making, with 18.9%. Furthermore, the role of IT staff is seen as the third observed category in EU1, with 17.2%. Nevertheless, the importance of organisational culture was not observed in EU1.

MU1: data shows that the Data scientists are the higher observed category in MU1 with 34.9%. The second higher observed category is the significance of OC. Then, the roles of information technologies such as BDS in improving executives' decisions. In Saudi Arabian universities, with 18.9%. However, IT staff and their roles in improving decision-making have not been observed in MU1.

WN1: in WN1, the most observed category is IT staff and their roles in improving decision-making with 17.2%. However, the impact of data scientists, information technologies such as BDS, and organisational culture have not been observed in WN1.

After discussing the appearance of categories in percentage, we would like to provide the participant's points of view and their experiences regarding the abovementioned categories in the next sections.

As SU1c stated that

"Data scientists or staff cannot perform anything without the help of new technologies. These technologies help them to analyse the data and present it to decision-makers. In my university, in every meeting, the decision-makers decide based on the data they analysed or provided by IT staff. These data would not be presented without the help of technology. So IT staff could not improve decision-making unless they use the technologies to support SU1c."

WN1b also addressed that,

"Technologies have softened the way we live; people being assisted by the technologies, IT staff and data engineers are human; without the help of the software that helps them to make decisions, they cannot make any decisions, make decisions you have to gain the data analysed big data. Therefore, there is no direct impact on people to improve decision-making. Technologies must be in between to help them. So. I believe there is no impact from IT staff to enhance the decisions of our top management. WN1b"

On the other hand,

"Well, the first thing I think is that they must have deep knowledge of computer science skills. Data scientists deal with very complex projects, so they must know at least part of the data science world, such as planning and communication skills, and may work with other employees, such as business analysts, who have experience in the commercial field then they might have the abilities to improve the decision-making, I am talking about the data scientists, yeah beware of these criteria, will have the significance of BDP on improving the decision-making WN1a."

NU1a addressed the significance of the new technologies in decision-making by top management,

"We have recently assumed the presidency of the university; as soon as he took over the academic leadership of the university, came to the technical side, and all of them are people who specialize in the field of technology in various disciplines, people most of whom have high experience in the field of technology and in areas that are artificial intelligence areas and I measure given my colleagues and colleagues of course, and the areas of It is in the form of information technology in general. Once they were assigned administrative tasks, the university changed the matter of decision-making processes. Decision-making processes are now based on the use of modern technologies, which brought many licenses for use at the university. They now include many topics for modern technical systems that contribute to decision-making."

In the next section, the author discusses the chapter summary.

7.15. Chapter Summary

This Chapter showed how we analysed the data from our interviews. It provided a cross-case analysis of BDA's social & technical aspects, which improved top management's decisions. Besides, the data provided the most critical features of both social and technical impacts towards enhancing executives' decisions in Saudi Arabian universities.

The social impact, such as BDP and organisational culture, positively influenced technical aspects such as SEC, including big data security, privacy, and security. The Chapter explains the connection between different types of social factors, such as the influence of OC on BDP. It found that OC positively impacts BDP in accepting and adapting to BDA technological enhancements. Finally, this Chapter talked about how technical aspects such as the security of big data and BDT influence the decision-making by top management. The data showed that technical factors of big data analytics positively influence decision-making. Finally, the Chapter also provided and discussed the new pattern revealed during the interviews.

Chapter 8

The Connections between Quantitative and Qualitative Results

8.1. Introduction

This chapter aims to corroborate the quantitative data findings obtained in the study's first phase with the qualitative findings derived from the study's second phase. To accomplish this, we extensively investigated the proposed research framework through an in-depth exploratory analysis of the model variables. Additionally, the corroboration revealed that the qualitative findings were consistent and congruent with the quantitative findings, which increased the study's conceptual validity and overall research consistency. Finally, we gleaned new insights, patterns, and insights from the rich data through an exploratory inquiry.

8.2. The Relationship between BDP and BDS

This section examines the relationship between BDA (BDP) performers and big data system quality (BDS). BDP included (1) IT staff who were either academic staff or non-academic staff; and (2) data scientists. On the other hand, BDS focused on key dimensions of big data systems, including privacy, security, and system quality. First, we provide a project sub-construct interaction between BDP sub-constructs and BDS dimensions.

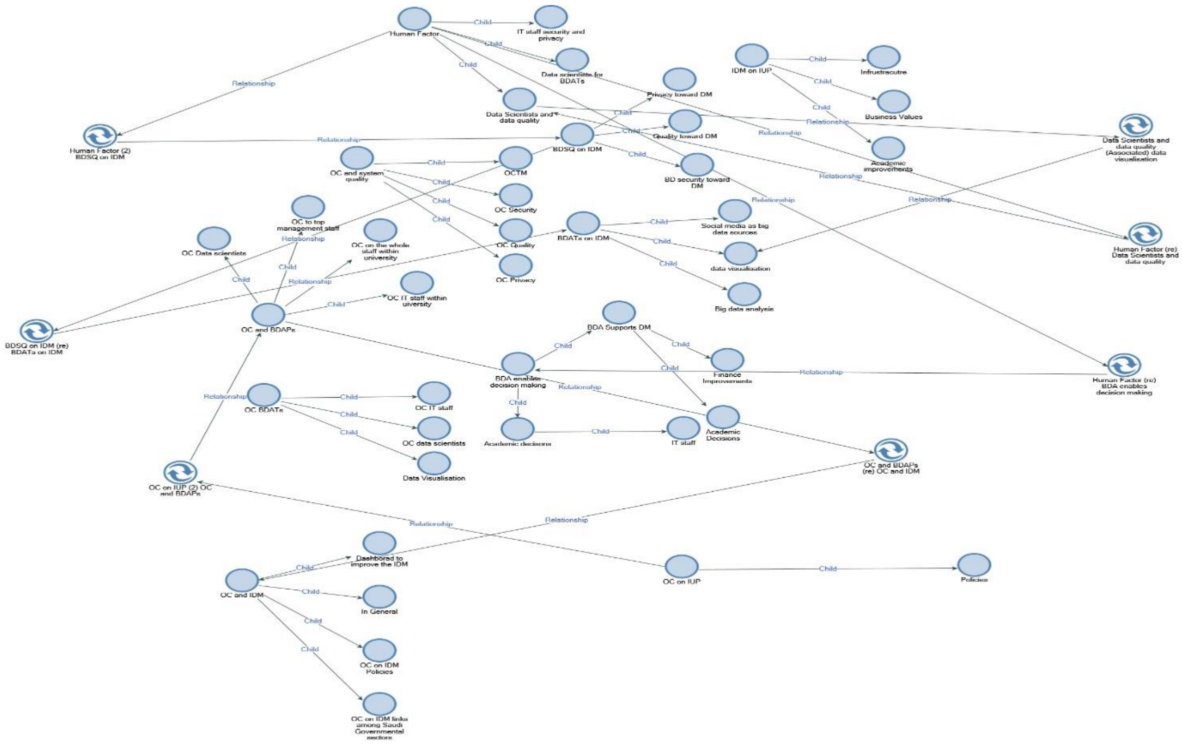

Figure 8.1. The relationship between the nodes and themes in N-Vivo 12

Big data performers refer to IT staff engaging with or being accountable for BDA and BDS. We tested the effect of IT staff on BDS. IT staff include data scientists responsible for ensuring big data quality. We hypothesised that big data performers positively impact big data security and privacy, whereas data scientists positively influence big data quality.

Participants from SU1b point out that "information security in recent years has become important in any firm. Before developing any system, I will make sure that the system meets the information security standard and then consider other system features. The same goes for IT staff in our university; they secure internal and external servers, and I believe they play crucial roles in securing our data".

For big data privacy, IT staff are concerned about its privacy. They update the privacy standards of the collected data or even the data we have on our servers. In our university, we are always improving the current technological aspects to gain the benefits of such technologies and big data analytics. MU1b highlights big data as new technology, and of course, one of its challenges, to the best of my knowledge, is security. Therefore, recently, we have focused on improving the security and privacy of the system as a whole concern. Some of our data is stored in the cloud so that the data will be in a safe place. Our concern here is information security within the university's servers, the daily activities of this IT equipment, access control and authorisations for accessing the data. In my opinion, the IT staff in our university are the main factor in securing big data and privacy.

A participant from, EU1b, who is working as an information security engineer, mentioned, "In my university, IT academic staff play an important job in securing the university system as a whole as well as the big data system. We have a monthly and weekly report on the security status."

Participants discussed the significance of data scientists in producing relevant, analysed data for senior management to make the best decisions possible. For instance, WN1a and WN1b stated, "What I noticed recently has become an official job as a data collector or a scientist. It has become a recognised job and has a job title. It was just that it collects data and provides it, but I am interested in the issue of data quality from the side of development and quality, that data scientists should be aware of the standard of data quality. Table 8.1 illustrates the relationship between BDP (IT staff), related hypothesis and supported qualitative findings.

Table 8.1. The Impact of IT staff on the security (SEC) and privacy (PRI) of big data.

Factors	Quantitative Hypothesis	Qualitative Supporting Evidence
The impact of BDP (IT staff) on big data security and privacy.	H1a: Big data analytic performers, including IT academic staff, and IT non-academic staff, have a positive effect on big data security. H1b: Big data analytic performers, including IT academic staff, and IT non-academic staff, have a positive effect on big data privacy.	"Information system employees, either academic or non-academic staff, participate in protecting big data; they secure the data. However, the academic staff they not fully engaging the big data security; we are relying on non-academic staff for big data security and privacy" (WN1a). "In my university, IT academic staff play an important job in securing the university system as

	H1c: Big data analytic performers, and data scientists, have a positive effect on big data quality.	a whole as well as the big data system. We have a monthly and weekly report on the security status". Furthermore, one participant stressed the need for data scientists to ensure massive data quality. The interviewee stated that storage is regarded as the first step in the analysing process. If we go through a stage, one of the fundamentals is to pay attention to the quality of data because poor data will harm the objectives for which it was analysed. And data scientists are in charge of this." MU1a.

8.3. The Relationship between BDP and BDT.

Besides the influence of IT staff on big data quality, this study also explored the impact of data IT staff that include data scientists on tasks of big data analytics, i.e., storage, analysis, and visualise. We considered these factors due to the significance of storing good quality data, the techniques used for storing it, and analysing those data and visualising them in an effective way that helps top management staff make the best decisions based on those analysed data. For instance, "data storage is considered an initial stage in the analysis process. If we go through a stage, one of the basics is to pay attention to the quality of the data because if the data is of poor quality, it would negatively affect the objectives for which it was analysed. Furthermore, this is the job of data scientists" (MU1a).

MU1b points out that “as you know, technology has automated almost everything; therefore, storing big data is automated, and data scientists will not engage in this process. About analysing and visualising, certainly, I will say yes because it is the main skill that data scientists should carry out. For example, during our weekly meeting, I tried to reduce the text and replace them with graphs and charts. It helps my colleagues interact more with the data I have presented. So, yes, data analysis and visualisation, from my point of view, should be the core task of data scientists".

However, participants SU1a, and WN1b, opined a strong indication of the role of data scientists in big data tasks. The participant stated that "for tasks such as storing, analysing and visualising, yes, it is the role of data scientists because they are the specialists and can do these tasks. They have a background in using the tools that are used. They are the people who can read the result and present the analysed data to the decision-maker." SU1a. In the same line, WN1b states, "yes, it should be the responsibility of the data scientist since he/she knows the data being collected then analyse, visualise it for better decisions. Stored data quality will make the data analysis and visualisation more effective, leading to better decisions" WN1b". These indications from participants support hypothesis 2. The table below summarises the influence of data BDP on BDT, related hypotheses and the supporting qualitative findings.

Table 8.2. The findings related to the impact of BDP on BDT

Factors	Quantitative Hypothesis	Qualitative Supporting Evidence
The impact of BDP on big data tasks.	H2: Big data analytic performers positively affect storing, analysing, and visualising big data.	"It is in an overlap between the task of a data scientist and between the data engineer. The data engineer is often responsible for storing the data, but this does not mean that data scientists cannot collect and analyse the data. Displaying the data is also one of the tasks of data scientists, the last level of data analysis" WU1a. "Data storage is considered an initial stage to start the analysis process. If we go through a stage, one of the basics is to pay

		attention to the quality of the data because if the data is of poor quality, it would negatively affect the objectives for which it was analysed. And this is the job of data scientists" MU1a. As you know, technology has automated almost everything. Therefore, storing big data is automated, and data scientists will not interfere in this process. If you ask me about analysing and visualising, I will certainly say yes because it is the main skill data scientists should carry out. For example, during our weekly meeting, I tried to reduce the text and replace them with graphs and charts. It helped my colleagues to interact more with the data which I presented. Yes, data analysis, visualisation in my point of view, should be the core tasks of data scientists.

8.4. The relationship between organisational culture and BDS

The results of research question 1a are presented in this section. The research question digs into the impact of organisational culture (OC) on big data system quality, including security, privacy, and data quality. In this study, organisational culture is defined by how the institution accepts and adapts to technological advancements, especially those associated with a data-driven orientation, such as enabling BDA and system quality. The influence of organisational culture on big data security, privacy, and quality is discussed first. Then, we discuss the respondents' perspectives on the influence of OC on the big data performers and the influence of OC on the tasks of big data, i.e., storage, analysis, and visualise. Then, the effect of organisational culture in enhancing decision-making will be discussed, and finally, how OC improves university performance.

A respondent states, "the process of accepting and adopting big data technologies depends on the university's decision-maker and his personality, mainly on the extent of his awareness of the importance and analysis of data. When the organisation's view is based on data and analysis." (MU1b). Similarly, the interviewee said, "yes", I believe the university will accept the new technological improvements that include security privacy and quality of big data, it will enable it because these improvements are supported by the country vision 2030." (WN1b).

On the other hand, participants from WN1a stated that there is no impact of OC on the big data system. He highlighted, "from my point of view, it has no effect because it is related to technology more and not at the level of individuals (employees). The organisational culture does not have an effective role in the issue of technological improvements such as security." Another participant, SU1b, indicates that "organisational culture, to the best of my knowledge, does not influence big data system quality. It does not even play any major effect on any technology. Although the participants' view regarding the impact of organisational culture on big data system quality includes big data security, privacy, and quality, the majority of participants concur about the significance of OC on big data system quality.

The above agreements appear to negate the results of quantitative findings, which indicate no relationship between OC and big data system quality Table 8.3 highlights the influence of OC on BDS, equivalent hypothesis, and supported evidence from qualitative results.

Table 8.3. The impact of OC on big data system quality.

Factors	Quantitative Hypothesis	Qualitative Supporting Evidence
The impact of OC on big data system quality	H3: Organisational culture to accept and adapt to technological enhancements has a positive effect on big data system quality, including big	"Security of big data is vital; in our university, one of the top management requirements is data security. Our university's president focuses on the technologies; therefore, this is

	data security, privacy, and quality	considered as the organisational culture because it comes from top management" (WNUa1). I believe that organisation culture will influence the privacy of big data. For example, in our university, at big data system, no one will have access to view stored data records, such as names or sensitive information" (UN1a). "Nowadays, data is the power that distinguishes you among others; if you have big data, but it is not a good quality data serve the plans and goals of the university, then it is useless" (WN1a).

8.5. The relationship between organisational culture and BDPs

The following section compares the results of question 1a, which examined the impact of organisational culture on big data analytics performance, particularly among IT employees and data scientists. The data collected from the participants provide a strong indication of the impact of OC on BDP. For example, one interviewee stated, "The answer is yes, positions, tasks force within the organisation (organisational culture) facilitate the staff's productivity. Since everyone knows the organisational culture and it the main guider for the performing the tasks by IT staff" (EU1a), likewise, "Yes, accepting new technological improvements will allow the IT staff to comply with the university top management guidelines and plans encourage the IT employees to participate in big data security and privacy " (WN1a). Also, participant SU1a says, "yes, the university administration or the decision-makers in the university, if they accepted this decision. It will certainly greatly influence a different level within the university from top to bottom." Another participant explained, "The answer is yes, positions, tasks force within the organisation (organisational culture) facilitate the productivity of the staff since the organisational culture is known by everyone and it the main guide for the performing the tasks by IT staff" (EU1a).

Regarding the impact of OC on big data performers, specifically data scientists, we noted the following. This influence involves how organisational culture effect data scientists in performing daily tasks. Participants from different studied cases produce their opinions on the influence of OC culture on data scientists. For example, "When we talk about organisational culture on data scientists, organisational culture will allow them to make more insights of the data they are dealing with, which leads to better decisions" (WN1b). The agreement among the participants supported the hypothesised relationship that indicates a relationship between OC and BDP. Table 8.4 summarises the Quantitative and Qualitative results depicting the impact of OC on BDT.

Table 8.4. The impact of OC on BDP

Factors	Quantitative Hypothesis	Qualitative Supporting Evidence
The impact of BDS on DES	H4: Organisational culture to accept and adapt to technological enhancements has a positive effect on big data analytic performers, such as data scientists	"Yes, the university administration or the decision-makers in the university, if they accepted this decision. Certainly, it will greatly influence different levels within the university, from top to bottom. I mean, organisational culture will influence every level that looks at the level above. It will force it to the lower level until it includes all the levels in the university. As a result, it will change the whole university to deal with data analysis for any decisions" (SU1a). "Yes, the university administration or the decision-makers in the university, if they accepted this decision. It will greatly influence different levels within the university from top to bottom" (SU1a).

		"Yes, the university administration or the decision-makers in the university, if they accepted this decision. It will certainly greatly influence different levels within the university, from top to bottom. I mean, organisational culture will influence every level that looks at the level above. It will force it to the lower level until it includes all the levels in the university. As a result, it will change the whole university to deal with data analysis for any decisions" (SU1a).

8.6. The relationship between organisational culture and BDT

In this section, we compare the findings related to research question 1b, which attempts to explore the influence of organisational culture on big data tasks, namely, storing, analysing, and visualising. The majority of the participants in the cases stated that organisational culture impacted big data tasks. Participants noted, for example, that OC encourages institutions to store, analyse, and visualise massive data to make wiser decisions. "Yes, organisational culture is critical because it helps us to store, analyse, and visualise data within our systems, allowing us to use those data in our university." (EU1a). These findings support the hypothesis that organisational culture impacts big data tasks such as storing, analysing, and visualising big data.

Table 8.5. Findings on the influence of OC on BDT

Factors	Quantitative Hypothesis	Qualitative Supporting Evidence
The impact of OC on big data tasks	H5: Organisational culture to accept and adapt to technological improvements positively affects BDT.	"In my opinion, as the decision-maker, yes, organisational culture represented as the enabler of storing, analysing, and visualising data from various resources will improve the decision making. It will allow the data scientists or engineers to store, analyse, and visualise the data from different places for better decisions. This applies to the organisations in the early stage of implementing BDA for improving top management decisions" (UWN1b). Organisational culture is very important because it allows the storage, analysis, and visualisation of the data within our systems; therefore, we can take advantage of those data in our university" (EU1a). Yes, it will lead to the process of improving the performance of the university, as data analysis will give indicators that help us make a decision, for example, making a decision based on data analysis in need to open new specialisations in the Faculty of Computer, opening cafeterias in the area where students gather, and so on. It also applies to

		personal decisions at work that helps to develop job performance. So, for example, this data will lead to good decision-making that analyses that huge data SU1d."

8.7. The relationship between organisational culture and DES

In this section, we discuss organisational culture's impact on improving top management's decisions in the Saudi Arabian institution – research question 1c. Several participants provide solid evidence of organisational culture's impact on the executives' decisions in higher education. For instance, EU1c indicates that "in my aspect, decision-making is a long process. It involves numerous factors, not only organisation culture, yes it is important, but many aspects influence decision-making. As I am one of the top management staff, as a decision-maker, I make my decision after a deep analysis of not only one factor as organisational culture".

Similarly, MU1d explains that "organisational culture of accepting new technology is crucial, but I did not see it as important as impacting the decision. Why? Because beliefs vary from one person to another, as a culture also, here in Saudi, people are scared of new changes, such as new technology or new guidance for accepting newcomers. That is why I disagree with this statement". Table 8.6 highlights the influence of OC on DES, the related hypothesis, and supported qualitative findings.

Table 8.6. Findings on the impact of OC on DES.

Factors	Quantitative Hypothesis	Qualitative Supporting Evidence
The influence of organisational culture on improving the decisions of senior management.	H6: Organisational culture, i.e., accept and adapt to technological improvements, has a positive effect on improving the decision-making by top management.	The organisational culture of accepting new technology is not only one process from top management; it should be from each level within the university. I mean, you support it from the

	.	junior employee to the upper level. I mean that organisational culture should come as one package of aspects like the organisational culture on staff, relationships, beliefs, and on us as top management staff. So yes, it should be from the upper level to the bottom. However, this strategy does not work based on my experience. So organisational culture does not only influence decision making; it is a group of factors that should come together" (WN1C). "In my opinion, organisational culture will not work on improving not only decision-making but also any process in university unless there is readiness from the whole considered people in our university."

8.8. The relationship between organisational culture and OP

One of top management's most crucial aspects is improving organisational performance. Therefore, the organisational culture must be considered to improve the organisation's overall performance. Thus, this section discusses the findings related to the impact of organisational culture on improving university performance. Participants from different cases strongly indicated the significance of organisational culture for improving university performance. For instance, participant UN1c indicates that accepting improvements means that we have top management support organisational culture; from this end, accepting such big data enhancements will improve university performance.

Similarly, “we have key performance indicators in our university, and based on collected data that identify top management performance, we found that employees are willing to accept and adapt to new technological or internal changes. As a result, such acceptance from the entire staff will improve our university performance” (SU1b). These findings support proposed hypothesis 7, which indicates that the organisational culture positively affects university performance. Table 8.7 highlights the influence of OC on OP, related hypotheses and supported qualitative findings.

Table 8.7. Findings on the influence of organisational culture on university performance

Factors	Quantitative Hypothesis	Qualitative Supporting Evidence
The impact of OC on big data tasks	H7: Organisational culture to accept and adapt technological enhancements have a positive effect on improving university performance.	Ye.s, of course, big data analysis, which will improve the organisation's performance and transparency. Yes, all universities aim to improve academic (educational) performance. Big data analysis will improve the university’s academic performance. Improving technology performance will also definitely improve academic performance. Data analysis will also help bring in high-quality faculty members, which improves academic performance. An important point is also big data analysis helps open new specialisations at the university level to keep pace with the market's need for graduates of certain specialities. These improvements are tolerated by organisational culture.

		WN1c indicates that accepting improvements means that we have top management support organisational culture. From this end, accepting such big data enhancements will improve university performance. We do have key performance indicators in our university, and based on collected data that identify top management performance; we found that employees are willing to accept and adapt to new changes, either it is technological or internal changes. As a result, acceptance from the entire staff, of course, will improve our university performance.

8.9. The Relationship between BDS and DES

In this section, we discuss the findings of research question two, which explored the impact of BDS (i.e., big data security, privacy, and quality) on decision-making. Big data security means that decision-making is supported by a system that secures data and restricts access to such data exclusively to decision-makers. Privacy refers to protecting personal information such as medical records and other data linked with individuals. Big data quality refers to the system's ability to keep high-quality analysed data and make it available to decision-makers to make the best possible decisions.

Interviewees presented their opinions regarding the impact of big data system quality and its roles in improving top management's decision-making. For example, participants stated that the security of the big data system increases the effectiveness of the decisions being made since the system allows its users (decision-makers) to make decisions based on secured data accessible by authorised individuals. Another participant mentioned, "Sensitive data cannot be accessed by any top management staff except the decision-makers. Therefore, all of these activities will improve big data security" (NU1a).

Privacy was accorded the same significance as data security. For example, “data privacy allows the executives to make their decisions without considering personal information that can affect the decisions, i.e. personal relations or interests" (MU1a). Likewise, another participant also mentioned how big data privacy contributes to improving the decision-making by executives. The participant states, "The system allows the data scientist to put a stamp on any sensitive records that can identify the persons, so the decision-makers can make their decisions without knowing any names written in the reports." (WU1a). Table 8.8 highlights the influence of BDS on DES and the associated qualitative findings supporting this hypothesis.

Table 8.8. Findings on the impact of BDS on DES

Factors	Quantitative Hypothesis	Qualitative Supporting Evidence
The impact of BDS on DES	H8: The quality of big data systems, including big data security, privacy, and quality, has a positive impact on improving the decisions of top management.	"This is nature. Good analysis leads to effective decisions. Today data is everything. Now the government is analysing big data for gaining good decisions" (WU1b) Correspondingly, one participant asserted, "When it comes to the quality, the higher the quality of the data, the better decision you can make" (NU1a). Equally important is that various participants highlighted the importance of big data quality in improving decision-making. For instance, one interviewee stated, "Let us say about the system in general, yes, one of the most important factors of decision-making is the speed of decision-making at present. If there are no systems that allow saving the analysed data of high

		quality, the presence of systems of this type will certainly lead to improved decision-making. Decision-making at present depends on data quality, for example, returning to the in-person study, and some other decisions, such as the distribution of faculty members, depending on data collected and analysed to make the decision. This confirms that the quality of the analysed data has a major role in the issue of decision-making at all levels in the university" (WN1a).

8.10. The relationship between BDT and DES

This section compares the quantitative and qualitative findings of research question two, which examines the impact of BDT on decision-making. BDT refer to storing big data from various credible sources, analysing that data from numerous sources, and visualising that data for better decisions. Hypothesis H9 stated that Big Data Tasks BDT, including storing, analysing, and visualising, have a positive effect on improving the decision-making by top management.

However, the findings from quantitative results indicate that big data tasks have no impact on improving the decisions of executives in higher education. On the other hand, the qualitative findings strongly support the significance of BDT toward improving decision-making. For instance, one participant highlighted, "The variety of this data will allow the managers to generate effective decisions because the analysed data comes from different sources" (WU1a). Similarly, SU1a explains, "Yes, I support that the data comes from various resources for data analysis; for example, data that comes from the ministry of education regarding new regulations is very effective for us to make our decisions based on such data". Table 8.9 highlights the influence of BDT on DES, the related hypothesis and the supporting qualitative results.

Table 8.9. Findings on the impact of BDT on DES

Factors	Quantitative Hypothesis	Qualitative Supporting Evidence
The impact of BDT on DES	H9: big data tasks, i.e., storing, analysing, and visualising, have a positive influence on improving the decisions of executives.	Participants mentioned the visualisation of analysed data. For example, MU1a stated, "Naturally, since we need to store good data for analysis and then visualise it to make the best decisions. Also, data sources have to be reliable to make the best analysis then best decisions" (NU1b). "The variety of this data will allow the managers to make the best decisions because the analysed data comes from different sources" (WU1a). "Those tasks, if not managed well by data scientists for choosing the best data storage criteria, can be gained by understanding why I am collecting the data and what kind of decisions these data can support. If these steps are involved before big data tasks, then it will improve decision-making WU1c". "It certainly has a big role now, with the government linkage, data collection has become an easy and easy process, and when organisational culture is added to it, it will surely have great

		benefits on the administrative and technical side. For example, data collection and analysis on new technology tools have a larger, faster and more effective role than data collection is done manually or traditionally, so to speak. Even at the level of employees in data analysis, the techniques gave them a great opportunity to analyse the data and present it in an attractive way to the decision-maker and even in a shorter time SU1b

8.11. The Relationship between DES and OP

The quantitative and qualitative findings on the impact of decision-making on a university's performance are discussed in this section. Improving the decision-making in this study is divided into three categories – i.e., improving financial decisions, enhancing strategic decisions, and improving academic decisions. Improved decision-making could be associated with a university's performance in creating business value and academic outcomes. The findings of both methods support the hypothesis that top management's financial, strategic, and academic decisions positively affect university performance. Interviewees gave their views on the impact of DES on OP. For example, participant WU1b mentioned, "Any decisions that concern the top management will improve the overall university performance. In the same line, another participant mentioned that "in my opinion, it will improve the university performance mostly in the academic field, if your academic part improved it will lead to improving the overall university performance" (SU1a). Table 8.10 highlights the influence of DES on OP, related hypothesis and related supported qualitative findings.

Table 8.10. Findings on the relationship between DES and OP.

Factors	Quantitative Hypothesis	Qualitative Supporting Evidence
The impact of DES on OP	H10: Improving decisions-of top management positively influences university performance.	"Improving strategic decisions will enhance the performance. It will allow me to make a strategic plan for the IT developments in the next five years. What new tools are needed for the new technology" (WU1b). More importantly, the majority of the participants believe that improving academic decisions by top management will improve university performance since it is an educational institution, and the main objective of such organisations is to enhance their performance associated with academic outcomes. For example, one participant stated that, “Our university consider an educational institution; enhancing our academic decision lets our university improve its position by focusing more on improving the current performance. How are we performing this year? How about next year? It is a kind of guide to achieving our goals and plans" (MU1a).

8.12. Comparing Quantitative and Qualitative Results: A Summary

Lastly, we compare the qualitative findings regarding the relationship between the social and technical factors as hypothesised in the research model. Semi-structured interviews supported all hypotheses except for two hypotheses. The table below shows a comparative overview.

Table 8.11. Comparing Quantitative and Qualitative findings of Proposed Model

Research Question and Objectives		Quantitative Results		Qualitative Results
RQ1: How does the social subsystem for big data analytics affect top management's decision-making and a university's performance?		**Hypothesis**	**Hypothesis Findings**	**Validated through interviews**
Social Construct of BDA				
a	To what extent do Big Data Analytic performers BDP, namely IT staff, and data scientists, influence BDS, i.e., big the security, privacy, and quality of big data in Saudi Arabian universities?	**H1**: ITs → BDS, BDP, BDQ	Supported	Supported
	To what extent do BDP affect BDT	**H2**: BDP→ BDT	Supported	Supported
b	To what extent does organisational culture affect BDS, i.e., security, privacy, and quality?	**H3**: OC→ BDS	NOT Supported	NOT Supported
	To what extent does organisational culture affect BDAP, such as IT staff and data scientists?	**H4**: OC→ BDP	Supported	Supported
	To what extent does social factors, namely organisational culture, impact BDT?	**H5**: OC→ BDT	Supported	Not Supported
c	To what extent does organisational culture influence the decision-making by top management?	**H6**: OC→ DES	Supported	Not Supported
	To what extent does organisational culture affect a university's performance?	**H7:** OC→ OP	Supported	Supported
d	To what extent do Big Data Performers affect the Decision-Making by top Management	**H11:** BDP→ DES	NOT Supported	NOT Supported
Technical Factors of BDA				
RQ2: How does the BDA technical subsystem, particularly BD system quality and BDT, affect top management's decisions in HEIs?				
	To what extent do BDS, namely big data security, privacy, and quality, enhance top management's decisions in HEIs??	**H8:** BSQ→ DES	Supported	Supported
	To what extent do big data tasks of big data, enhance top management's decisions in HEIs?	**H9:** BDT→ DES	Supported	Supported

Outcomes Improving Decision-Making & University Performance			
RQ3: To what extent does BD-driven decision-making influence a university's performance?	**H10:** DES→ OP	Supported	Supported

As mentioned in the table above, the research questions were replied and provided detailed answers to those research questions. For instance, research question 1 which south to answer that to what extent do Big Data Analytic performers BDP, namely IT staff, and data scientists, influence BDS, i.e., big the security, privacy, and quality of big data in Saudi Arabian universities? The hypothesis 1 proposed that IT staff have appositive impact on big data security, privacy and quality and this hypothesis were supported in quantitative and qualitative findings. Besides, research question 1c explored to what extent does organisational culture affect BDS, i.e., security, privacy, and quality? And the proposed hypothesis was not supported in both quantitative and qualitative findings, which allow us to conclude that organisation culture does not have an impact on big data system that include security, privacy, and quality. Regarding research question 1 d

Research question which sought to explore that to what extent do Big Data Performers affect the Decision-Making by top Management. The findings of the quantitative and qualitative were not support the proposed hypothesis. The results of this hypothesis concluded that big data performers do not have an impact on the decision-making by top management in Saudi Arabian universities.

Besides, research question 2 was sought to explore How does the BDA technical subsystem, particularly BD system quality and BDT, affect top management's decisions in HEIs? The hypothesis of this questions were proposed that big data system and big data tasks have a positive impact on improving the decision-making by top management. The findings of this proposed hypothesis were supported in both quantitative and qualitative results.

Lastly, the findings of research question 3 were sought to answer to what extent does BD-driven decision-making influence a university's performance? The hypothesis proposed that big data systems and big data tasks include storing, analysing and visualising big data will improve the decision-making by top management in Saudi Arabian universities. These proposed hypotheses were positively impacted the decision-making by top management in both quantitative and qualitative findings.

Thus, the findings of the proposed hypothesis will assist the researcher in higher education, and provide the direction of the future research confidently, and based on quantitative and qualitative data. Further recommendations and future direction of this study will be discussed in the next chapter.

8.13. Chapter Summary

This chapter presented a comparison related to the findings of quantitative and qualitative methods. Quantitative data were gathered using a survey. On the other hand, in qualitative methods, data was gathered through semi-structured interviews. The comparison of collected data includes the tables highlighting the hypothesis and findings of both methods. In the end, the author provided a table highlighting research questions and quantitative findings on research hypotheses and corroborating qualitative findings to confirm the acceptance and rejection of hypotheses and the overall conclusion. Overall, qualitative findings illustrated the research model and supported most of the quantitative findings.

Chapter 9

Implications, Discussions, and Conclusion

9.1. Introduction

This chapter revisits the quantitative and qualitative evidence presented in Chapters 5, 6, and 7 to discuss socio-technical aspects of big data analytics and their role in executive management decisions in HEIs. The chapter begins by revisiting the research problem; then discusses the findings and contributions of this study. Next, the implications and limitations are discussed, and the chapter ends with future work and a conclusion.

9.2. A Brief Overview: Revisiting the Research Problem

The increasing amount of data generated and stored electronically demands new tools and technologies to leverage the advantages and business value. Recently, organisations realised the importance of using BDA to achieve businesses' objectives. However, implementing such technology remain challenging due to social and technical complexities. Cervone (2016) stated that organisations tend to overly focus on technical aspects and ignore other imperative aspects, such as social factors, when implementing big data analytics. Existing studies (Bostrom & Heinen, 1977; Dremel et al., 2017) have emphasised how work systems combine social and technical dynamics, and none can be favoured over the other.

Various studies highlighted the challenges faced in implementing BDA through the socio-technical lens. For instance, Halford & Savage (2017) stated that various firms face a lack of technical expertise, applications, infrastructure, and work procedures to effectively use, manage, and explore the data to generate valuable insights. Similarly, Gerber (2018) discusses HR professionals' core issues in assessing BDA. These issues primarily arise due to a lack of technical understanding of BDA. Other studies (Alharthi, Krotov, & Bowman, 2017; Thirathon, Wieder, Matolcsdy, & Ossimitz, 2017) have noted that administrative personnel rarely perceive the value of BDA, while business leaders and decision-makers are clamouring to find qualified data scientists with the required skills. Ignoring institutional structures such as data governance and their potential impact on managerial decisions is also challenging (Alharthi, Krotov & Bowman 2017).

Several other concerns have been raised, including people's inability to utilise IT tools due to rapid technological advancements (Wood & Leone 2015). Moreover, there is insufficient workforce training to deal with the latest technology to execute complicated operations where stress and resistance may play a significant role (Nick 2018). While change theory has focused on the event's failure or success, it has not concerned the people as the main factor for change (Andrea De Mauro, Marco Greco & Grimaldi Michele 2016). Moreover, Nelson & Winter (1982) revealed that technology is not independent of people and other institutional factors such as leadership and management guidance.

BDA for decision-making is challenged by the lack of trained and skilled data analysts and the lack of awareness (Albanna & Heeks 2019). One of the stumbling blocks is the lack of an education and training framework that can be applied to developing considerable BDA skills to support decision-making and education processes (Fosso Wamba et al., 2016). Such skills include understanding and analysing large amounts of data efficiently and creatively (Ahmed 2016). Additionally, there is a need for data scientists, business analysts, data engineers, and big data analysts within organisations to maximise the benefits of the data stored in servers (De Mauro et al., 2016).

This study aimed to provide a theoretical and practical framework for using BDA to improve strategic decision-making in HEIs. Such a framework, as a result, assists the researchers and practitioners in gaining a deeper knowledge of the connection between BDA's social & technical subsystems in supporting decision-making processes.

9.3. Discussing the Key Findings

Socio-technical aspects of BDA are vital to improving executive decisions and enhancing firm performance. The social aspect of BDA has been investigated in previous studies, specifically the role of organisational culture (Sam & Chatwin, 2019). However, in the context of Saudi Arabian higher education, no previous studies have examined the importance of social and technological aspects when using BDA to enhance executives' decisions. This phenomenon requires a contextualised understanding of the socio-technical of BDA in the lenses of human, technical, and organisational culture in higher education. This study delved into this gap to investigate the impact of human and organisational culture (social subsystem) and big data system quality (technical subsystem) for improving decision-making. In the next subsections, we will discuss the role of social factors – i.e., BDP and organisational culture, followed by technical factors – i.e., system quality (BDS) and tasks (BDT).

9.3.1. BDA Performers and Big data Security, Privacy, and Quality

Humans are central to BDA systems because they transform data into insights by aligning analytics to organisational processes, procedures, and goals (Fernando & Engel 2018). Recognising big data performers has been explored in previous studies (Hargiss & Member, (2017) that emphasise the importance of human factors in implementing new systems. Taking institutions of higher education, BDA performers are considered the academic and non-academic IT professionals accountable for big data security and privacy, as well as data scientists who are responsible for producing high-quality data for effective decision-making.

Our findings significantly support hypotheses that academic and non-academic IT staff affect big data security and privacy, emphasising the role of IT staff in ensuring security and privacy. Besides, the findings indicate that IT staff rely on the system quality to control and maintain big data privacy and security. Therefore, system quality should allow IT staff to perform big data security and privacy activities. The results also show that the collaboration of IT academic and non-academic staff is imperative in strengthening the security and privacy of big data within Saudi Arabian universities. Undoubtedly, social factors, particularly "Big Data Analytics Performers," i.e., IT academic and non-academic staff, significantly impact the technical aspects of big data security and privacy. Similarly, Jung (2017) emphasised the significance of human factors in big data security and privacy by highlighting big data issues in governmental organisations and how IT staff could solve them. Other studies (Russom 2011; Sivarajah et al. 2017) argue that IT systems and BDA systems are predisposed to the activities of IT staff. Moreover, Breckenridge (2020) emphasised how the perception and decision-making of information security staff shapes prevention strategies against cyber-attack.

Besides IT academic and non-academic staff, data scientists were considered the second most crucial big data performers. Data scientist was defined in previous studies as qualified and skilled persons who can convert raw data into meaningful and useful insights (De Mauro et al., 2016). For instance, Adrian et al.(2018) examined BDA implementation in various dimensions and how those dimensions affect decision-making. The authors specifically explored the impact of BDA implantation on knowledge workers and their roles in providing useful data for making effective decisions. Besides, Song & Zhu (2018) highlighted the role of data scientists as storing the data, performing data analysis, and visualising analysed data that assists exclusives in making their decisions. Orenstein, Ladik & Rainford (2016) indicated that a major component of utilising big data within organisation will not be only data collecting, but also considering the significance of big data quality on enhancing decision-making.

In this study, we hypothesised that data scientists positively influence big data quality. Hypothesis H1 was supported as we found a significant positive effect on big data quality. This finding denotes that Saudi Arabian universities may consider attracting more skilled data scientists to improve big data quality. This step will allow universities to improve top management's decision-making in Saudi Arabia. We considered the role of BDP in system quality, particularly BD security, privacy, and quality. We argued the central role of system quality in enabling top management decisions in Saudi Arabian universities. Data scientists were considered crucial in BDP because they must have effective roles in ensuring data quality. Similarly, Nadikattu R (2020) highlighted the primary role of data scientists in BDA, but we must appreciate other big data systems actors that will vary based on the context in which big data is applied. Invariably, decision-makers in HEIs must appreciate that human factors (BDP) influence big data security, privacy, and quality, which necessitates top management support for human involvement in BDA.

9.3.2. Organisational culture and Big Data Analytic Performers

Organisational culture is a key competence that encourages harmony between an organisation and its personnel's principles and is linked with organisational success (Azeem et al., 2021). The authors also highlighted that organisational culture could help organisations transform processes by aligning them with employee motivation and guiding them to become more valuable to the organisation. Accepting and adapting to new technologies was defined by Dasgupta & Gupta (2019) as the degree to which an organisation is adaptable and consistent, as well as how it empowers people to accept as well as adapt to new technologies to accomplish the organisation's goals.

Our findings indicate that organisational culture to accept and adapt to new technological improvements positively impacts big data analytic performers, i.e., IT staff and data scientists (H4). Accepting and adapting to big data analytics improvements would encourage IT staff to enhance system quality factors, i.e., big data security, privacy and quality. It could also allow data scientists to generate good data quality for enhancing executives' decisions.

Correspondingly, Alharthi et al. (2017) stated that organisational culture guides information systems development and motivates human actors such as programmers and other information technology staff within the organisation. Our findings reinforce the argument that organisational culture has become imperative to the performance of new technologies Dasgupta & Gupta, 2019), big data analyics (Upadhyay & Kumar, 2020), and with higher education as one of the rapidly growing contexts (Alblawi & Alhamed, 2017). Thus, Saudi universities must considered adapting organisational culture to guide IT staff and data scientists to accept and adapt big data analytics technological improvements.

Accepting and adapting to new technologies was defined by Dasgupta & Gupta (2019) as the degree to which an organisation is adaptable and consistent, as well as how it empowers people to accept and adapt new technologies to accomplish the organisation's goals. Besides, the organisational cultural values have traditionally been seen as a long-term base, enabling organisational staff members to identify changes and adjustments inside that particular organisation. While organisational culture cannot be completely altered, it could be adapted even better as organisations leverage existing cultures and capabilities to meet necessary changes. Organisation culture, which could emerge in official and informal forms, motivates employees and promotes innovative strategies (Vinh The et al., 2019). Adaptation enables the organisation to cultivate a digital culture among employees at different levels through a shared drive to accept new technologies, allowing organisations to achieve their goals effectively (Jarrah et al., 2020). This study denotes the significance of organisational culture in the social subsystem.

9.3.3. Organisational Culture and Big Data System Quality and Tasks

While the role of organisational culture in shaping big data professionals is established in the preceding section, we hypothesised the corporate culture as an aspect of the social subsystem on big data tasks (H5) and system quality (H3) as aspects of the technical subsystem. The STS theory emphasises the interactive impact of the socio-technical subsystems. Our findings offer evidence to support the tenets of the STS, particularly regarding the tasks performed. We noted that organisational culture positively influences common big data tasks of storing, analysing and visualising big data. Further still, organisational culture positively influences big data systems aspects such as security, privacy, and quality. From the qualitative data, participants explained that much as big data is power, the organisation's proclivity towards security and privacy could shape the value derived. They also indicated that organisational culture informs how the organisation engages with the data and drives the actions of its big data professionals.

Other studies have reported that cultural aspects, such as a preference for fact of the culture of making decisions, define the importance of big data to an organisation and how it would be engaged with the data (Alharthi et al., 2017). Technical aspects such as information security (Al-umaran, 2015; Lin & Luo, 2021), privacy (Alharthi et al., 2017), system sustainability (Dubey et al., 2017), and system success (Romi Ismail, 2011) are considered an integral aspect of the organisational culture. Our findings on H3 contradict the above views, including Romi Ismail (2011) 's argument that organisational culture influences system, service, and information quality – the technical aspects introduced by DeLone and McLeans' framework. Others have indicated that flexible cultural orientations encourage organisations to apply BDA in collaborative tasks (Dubey et al., 2019). We argue that cultural influences would be more prevalent on how organisations handle big data tasks, than system quality. Likewise, Alharthi et al. (2017) mentioned that organisational culture shapes how organisations deal with big data complexities such as collecting and storing data from multiple sources and formats, and keeping pace with the rapid growth of data. Our findings offer empirical evidence of the influences of institutional structures on big data systems and tasks.

9.3.4. Organisational Culture, Decision-Making & Performance

Organisational cultural barriers have posed significant issues in managing big data systems, which have raised the need for cultural change rather than cultural management (Alharthi et al., 2017). Cultural changes have been associated with accepting new technologies, such as big data systems (Alharthi et al., 2017); moreover, a data-oriented culture is associated with analytic-based decision-making (Thirathon et al., 2017) and improved firm performance (Arokodare et al., 2019). Motivated by the increasing recognition of organisational culture, we hypothesised that organisational culture positively influences decision-making (H6) and institutional performance (H7). Our findings supported these hypotheses and revealed that organisational culture ingrained at all levels of management and across all functional units positively influences big data uptake beyond experience. Similarly, Oesterreich et al. (2022) argued that with a suitable organisational culture, big data resources and capabilities would strongly impact the performance of multiple firms. However, qualitative accounts indicated that the role of organisational culture in decision making could be augumented by other factors such as organisational readiness on culture and decision-making. While we obtained a significant positive effect of culture on decision-making, the qualitative data accumulated did not adequately support this hypothesis. Also, there is that believes other underlying factors, such as BDA resources and infrastructure, could posit stronger influences. Nonetheless, other studies align with our quantitative findings and stated that decision-making culture is central to use BDA (Frisk & Bannister, 2017) and that organisational culture mediates the use of analytical knowledge in BDA (Upadhyay & Kumar, 2020).

Overall, when considering the role of organisational culture in utilising BDA for firm performance, the impact is undeniable; however, other underlying factors must be considered. Our findings revealed organisational readiness impacted overall firm's performance, while other studies pointed to external pressures, data quality and organisational capabilities (Oesterreich et al., 2022; Wamba et al., 2017). Others have categorically supported our findings to suggest that a combination of resources, including the data, people, technology, culture, and external environment, must be considered (Mikalef et al., 2019).

Regarding the BDA and decision-making, other studies have indicated that analytic-based decision-making or fact-based decision-making is associated with various opportunities that pave the way for enhanced performance (Aldholay et al., 2018). Others have argued that with dynamic capabilities and strategic business alignment, organisations are at the forefront of utilising BDA to enhance their performance (Wamba et al., 2017). Given such reports, we hypothesised that BDA-driven decision-making positively affects institutional performance (H10). Both the quantitative and qualitative accounts concurred that the increasing reliance on data-driven decision-making promotes the institution's financial and academic performance. This finding adds to existing literature proving this link in other contexts, such as BDA enhancing firm productivity in IT-intensive firms (Müller et al., 2018), how BDA lead to improved performance in Pakistani firms (Mariam et al., 2020), the advancement of BDA toward the performance of the higher educational firm in Malaysia (Ashaari,2020). Overall, our findings confirm the influence of BDA on the strategic decision-making and institutional performance of HEIs in the Middle East.

9.3.5. System Quality and Improved Decision-making (DES)

Big data's rapid growth has raised the need for BDA to collect data for effective decisions, especially at the executive level (Elgendy & Elragal 2016). Nowadays, consistency in strategic decision-making improves productivity (Adrian et al., 2018). In their seminal work on IS success, DeLone & McLean (2003) argued that system quality and information quality must be ensured to derive outcomes in job and decision-making performance. Normally, a high-quality system is user-friendly, easy to adapt, easy to use, and attractive. The quality of a BDA system revolves around common characteristics such as reliability, adaptability, accessibility, and privacy; information quality relates to completeness, accuracy, currency, and format (Ji-fan Ren et al., 2017). Moreover, the system's quality is crucial to handling data volume, velocity, and variety (Brynjolfsson & McAfee 2012). Besides, system quality enables transaction, transformational, and strategic value for the firm (Ji-fan Ren et al., 2017). There is evidence in developing countries that system quality affects transformational leadership, which inherently affects system use and firm performance (Aldholay et al., 2018).

BDA system quality focuses on building a secure system (Jung 2017). Information security contributes to effective decision-making and supports planning and execution procedures (Cavallo et al., 2019). Due to big data velocity, firms are responsible for managing the amount of big data stored (Wood & Member 2019). The velocity of big data raises concerns about big data quality (QUA), which is a critical success factor for an organisation's performance (Janssen, van der Voort & Wahyudi 2017). Undeniably, data quality allows business leaders to make better decisions faster (Trieu Van-Hau Thi & Arif 2018). Janssen, van der Voort & Wahyudi (2017) argue that BDQ not only depends on the sources of big data but also on the system's ability to generate good quality data to maximise the benefits.

Our findings on the significance of system quality in improving decisions show that privacy and quality in BDA significantly affect executives' decisions in Saudi Arabian HEIs. However, the effect of big data security was not supported, though security was also considered a quality aspect of BDA systems. Security goes hand in hand with privacy in any information system. Therefore, we hypothesised that big data security has a positive influence on improving decision-making. The rationale behind this argument is that controlled data access for top management staff (decision makers) would allow the decision makers to rely on secured data – i.e., data not manipulated by any other staff within the university. The survey findings, however, show that big data security does not influence executives' decisions in Saudi HEIs. One top management staff interviewed assumed that big data security is insignificant when considering university data (public data); however, another participant argued that security is imperative and that decisions could not be based on unsecured data. Undoubtedly, big data security is crucial for trustable decisions as it is believed to increase the decision maker's confidence in decisions.

Furthermore, big data is stored from various resources in different formats and often involves personal information; therefore, privacy considerations cannot be overlooked. An effective system allows IT staff to ensure data privacy; thus, we hypothesised that privacy in BDA systems positively impacts the university's financial, strategic, and academic decisions. The survey and interview findings supported hypothesis H8, which stated that big data privacy positively affects big data-enabled decision-making. With emerging technologies, privacy-preserving capabilities or privacy-aware systems are critical in data analytics (Geetha et al., 2020). Other studies have emphasised that improved data quality (including privacy preservation) allows for better decision-making (Cavallo et al., 2019; Trieu Van-Hau Thi & Arif, 2018). Moreover, the unthought-of benefits could involve boosting the confidence and trustworthiness of decision-making processes.

Taking into account how big data positively affecting decision-making (Cavallo et al., 2019; Hau Thi & Arif, 2018), strategic firm value (Ji-fan Ren et al., 2017) and organisational performance (Aldholay et al., 2018), we hypothesised that the quality of big data has a positive influence on improving the decision-making. The findings reveal interesting results. The survey revealed that big data quality positively impacts decision-making, which implies increased effectiveness of top management decisions in financial, strategic, or academic pursuits. The interviews also supported hypothesis H8c, where one participant mentioned adding it from the nodes of big data quality.

Overall, big data security, privacy, and quality are imperative features that should be considered in big data analytics among Saudi HIEs. Furthermore, considering the quality characteristics of the big data system can improve the decisions of Saudi institutions' executive management and ultimately enhance institutional performance.

9.4. Research Implications

Overall, the study expounded the socio-technical view on big data analytics and investigated how socio-technical factors of BDA interaction influence executives' decisions and institutional performance. In the contextual gap of BDA, the study also delved under the investigation contexts of HEIs in developing countries. Finally, focusing on the outcomes, we explored data-driven financial, strategic, and academic decisions and how they influence institutional performance.

9.4.1 Theoretical Implications

Earlier research has concentrated on a few problems, such as the effect of OC on collaborative performance (Dubey et al. 2019), the effect of corporate culture on analytical knowledge and BDA capability (Upadhyay & Kumar 2020), and gaining a competitive edge through organisational culture, knowledge sharing, and innovation (Thirathon et al. 2017). This study extends the body of knowledge of HIEs by examining the potential benefits related to socio-technical subsystems on executives' ability to make effective decisions in HEIs.

First, the study conceptualised the BDA social system using two factors: (1) the *BDA actors*, who are the big data performers such as IT academic and non-academic staff & data scientists, and (2) *institutional structures* such as organisational culture. The social realm promotes a comprehensive understanding of institutional and human factors in BDA and their role in shaping BDA systems and enabling decision-making and institutional performance. The BDA actors will include the technical and non-technical teams interacting with the institution's big data. Again, our study reconciles the technical and non-technical engagements in big data. The institutional structures in the context of BDA systems can be assessed as the institution's culture towards accepting and adopting technological advancements inherently geared towards promoting a data-driven culture. Generally, institutional structures will shape big data actors (both technical and non-technical), and the two forces will inevitably shape the institution's BDA practices and system quality.

Second, the study expounds on the technical realm of BDA by highlighting two core elements – i.e., the quality of the systems and the tasks undertaken. The quality elements will inevitably relate to prominent quality features, including data security, privacy, and quality. The less investigated aspects relate to BDA tasks, which revolve around the data lifecycle. Three core tasks can be defined – i.e., capturing, analysing, and visualising big data for decision-making.

Previously, the significance of information and system quality in work effectiveness Aljumah et al., 2021), big data security (Aseeri & Kang, 2020; Lombardo, 2018; Sollins, 2019), and big data quality (Ardagna et al., 2018) has been investigated. Such studies have laid the foundation but have not provided a complete view of BDA systems. A fragmented exploration of the technical aspects of data analytics could undermine the development of integrated approaches or frameworks. This study argues that a complete analysis of BDA systems consists of the *system quality* and the *tasks* undertaken. The system quality features will influence the big data tasks undertaken, where improved system quality could be associated with better execution of big data tasks.

Third, the interactive role of the social systems (i.e., actors and institutional structures) and technical systems (i.e., system quality and tasks executed) influence institutional outcomes. This study denotes that institutional structures (organisational culture) shape actors (big data teams) who ultimately influence the technical systems due to their inextricable and routine engagement with the systems. Notably, institutional structures manifest through actors; therefore, such structures alone may not directly influence the technical structures (system quality and task executed). Revisiting our corroboration of findings in Chapter 8, we noted that the survey and interview findings rejected the argument that institutional structures will directly shape system quality. Additionally, the interview reports rejected the idea that organisational culture influences the tasks executed. Undoubtedly, social and technical influences drive decision-making and institutional performance.

Lastly, the developed framework, which could also be relevant for other sectors, combines the strength of social and technological aspects in HEIs. The study explores the potential application and variation in BDA systems in higher education settings or between developing and developed countries. The study promotes contextual-aware exploration and theorising on emerging technologies since the diffusion of such technologies varies by factors such as national culture or digital economic growth. Overall, this research increases the body of knowledge on socio-technical theory (Wyatt 1981) and its application in emerging technologies. The study revealed the extent to which the social and technical structures are congruent in the culture of decision-making and institutional performance.

9.4.2 Methodological Implications

Although earlier studies explored the values of big data analytics in numerous fields, few studies investigated the significance of BDA in enhancing decision-making in the public sector. For instance, the studies by Trieu Van-Hau Thi & Arif (2018), Thirathon et al. (2017), Elgendy & Elragal (2016), and Shamim et al. (2020) have quantitatively examined the effect of BDA on improving the decision-making in public and private organisations. On the other hand, Janssen, van der Voort & Wahyudi (2017), Mcconnaughey & Member (2020), Frisk & Bannister (2017), and Osuszek & Ledzianowski (2020) have qualitatively explored how big data analytics enhances decision-making processes. However, even with the above studies, no studies have taken a mixed-methods approach to investigate big data applications. A few cases include Gangwar et al. (2022) and Intezari & Gressel (2017), who adopted a mixed methods approach and examined how BDA in digital transformation era, and the infleucne of BDA in improve executives' decisions respectively. A mixed methods approach allows the researcher to corroborate findings by triangulating different data types. Moreover, utilising the mixed methods approach generates in-depth understanding of the explored phenomena.

9.4.3 Practical Implications

The current study has practical implications too. We argue that organisational culture is central to the institutional structures that shape the use and outcomes of big data systems. Importantly, HEIs top management must recognise the role of organisational culture (as one of many social factors) in shaping big data workforce and systems. The role of organisational culture is more important in the big data workforce than the systems themselves. Organisational culture impacts employee acceptance and adaptation to new technological improvements, especially emerging technologies such as big data, which are still under intense exploration and inflated expectations (as theorised by the Gartner hype cycle). Organisational culture will not directly influence the quality of big data systems, but perhaps its effect manifests through its influence on the institution's big data teams.

Besides, Saudi Authority of Data and Artificial Intelligence has been launched in 2018 with the aim of

The findings of the current study could assist the decision-makers, researchers, planning teams and quality assurance in Saudi Authority of Data and Artificial Intelligence in identifying the current stage of BDA in Saudi higher education; and therefore, the possibilities of taking advantages of social and technical aspects that could enhances the current phase of BDA. Besides, SDAIA also could benefits form the findings of the current study in investigating the significance of human factors in BD environment. The significance of data scientists in higher education firms. Precisely, the importance of having data scientists (academic staff) in higher education because they know which data could use for further analysis that could improve the decision-making and enhance organisational performance.

Likewise, top managers must recognise and take advantage of merging academic and non-academic staff within HEIs, as these are key players in BDA systems. Merging these staff can positively allow the university to gain the experience of IT academic and non-academic staff in developing new big data systems or upgrading current systems. Another reason for merging IT staff is to get the benefits of the technical background of some staff for ensuring that big data in the BDA system is secured and private. Our findings suggest that employees in HEIs could significantly influence all aspects of big data systems, including system security, data privacy, and data quality. Moreover, the influence of employees could extend beyond system quality aspects to BDA tasks. This implies that institutions must strongly consider employees in developing and maintaining big data systems – thus, employee involvement and training are required.

On the technical side of BDA, institutions must pay attention to the security, privacy, and quality of big data, as such aspects will affect executives' decisions. The privacy and quality could also increase the decision-maker's confidence in making their decisions. Nonetheless, as previous studies also indicated in other contexts, practitioners in HEIs must appreciate that improved decision-making through BDA analytics could augment the overall institutional performance financially and academically.

Overall, HEI management must recognise the powerfulness of reconciling the social and technical factors in developing and maintaining BDA systems and practices. The technical developments may not stand alone without the appropriate planning and management of the social aspects, particularly the employees and organisational culture. Socially, HEIs can leverage the advantages of a culture of accepting and adapting technological advancements, which could ultimately manifest in a data-driven culture. Culture is closely associated with big data people. Therefore, managing BDA calls for recognising the unified role of all staff beyond data scientists – this includes defining the roles and responsibilities of academic and non-academic staff in managing big data. The rationale is that while data scientists may be responsible for ensuring data quality, the academic and non-academic staff could improve big data security as well as privacy. Notably, the institutional and human factors are central to deriving the benefits of BDA, given their influence on BDA system quality and tasks.

9.4.4 Sectoral Implications

Previous studies on BDA in decision-making (Shrestha, Ben-Menahem & von Krogh, 2019; Trieu Van-Hau Thi & Arif, 2018; Thirathon et al., 2017) are comparatively inapplicable across all sectors. While the studies of Elgendy & Elragal (2016), Chander (2019), Koŝcielniak & Puto (2015), Adrian et al. (2018), investigated the influence of BDA in private sectors, the studies of Yang et al. (2016), Alhamed (2017), Mukthar & Sultan (2017), Aseeri & kang (2020) explored the impact of BDA for decision-making in the public sector. This study presents a contextualised investigation focusing on HEIs (the case of Saudi Arabian universities). From a more generalised perspective, this study contributes to our understanding of how BDA is implemented in public institutions in developing countries. Add more text here

9.5. Limitations and Future Research Recommendations

Like other studies, this research has certain limitations. Although the current research findings could correspond more with STS theory, this research relied on data collected from Saudi Arabian higher education. Inevitably, the findings could be influenced by Saudi Arabian culture and values. The current study have shown the influence of cultural context on technology adoption and diffusion. Therefore, future studies could delve into contexts with different cultures to retest and validate the model and associated hypotheses. Although the model was tested in a developing country context, the results could differ across developing countries due to differences in national culture, IT infrastructural development, economic digitalisation, and digital divide, among other factors.

Another limitation could relate to the institutional reliance on social media platforms as a source of big data. In other words, social media were highlighted during the interviews as the mean source of big data since the data provided in social media platforms is structured data and can be easily analysed for faster and more effective decisions. Future studies could benefit from investigating the significance of social media as the source of big data and their contribution to effective and faster decisions. Therefore, while this study provides a deep knowledge of the big data analytics socio-technical aspects, future studies should consider a deeper investigation of big data influence on infrastructural development in enabling decision-making and organisational performance.

This study explores the influence of socio-technical aspects that support the implementations of BDA in Saudi higher education. Alternatively stated that Saudi Arabian context is different than other developing countries in culture values, organisational settings, believes. Therefore, future studies will benefit by exploring the diversity of culture and organisational settings in other developing countries. Not only in higher education context, but also in other field such as healthcare, supply chain management. Invariably, our findings and existing literature have reiterated the possibility that institutional structures, including organisational culture and the people, may not solely explain the role of BDA in improving institutional performance. With this argument in hand, there are two potential areas for further investigation. First, what organisational cultures facilitate big data technical systems? Investigating the facets or dimensions of culture that promote or inhibit the implementation and use of big data systems is imperative. Culture is not a thing but a set of values, beliefs, and patterns that could be dimensioned to provide a complete account of potential variations. In this study, we focused on a culture of accepting and adopting technological advancements; however, what could be the opposing cultural values, and how could they affect decision-making and firm performance in big data environments. Second, our findings and the literature concur that other underlying factors could account for BDA outcomes other than the social subsystem. Future studies could benefit from investigating organisational readiness and external factors.

The last limitation, which also applies to earlier studies, relates to the contextualisation and methodological investigation of big data studies. While this study focused on six universities, future studies could extend our findings by investigating other educational contexts to gain a broader understanding of the sectoral aspects of BDA in education. Undoubtedly, big data analytics has received greater interrogation on customer intelligence and supply chain performance in retail, banking, and financial industries, as Elgendy & Elragal (2014) reported. Other efforts have been geared toward health informatics. Additionally, while this study involved a mixed methods investigation, future studies could contribute by exploring big data through multiple methods to extend and corroborate findings. In the literature review, it was evident that very few studies have attempted methodological triangulation in studying big data applications – except for a few attempts, such as Mikalef et al. (2019). A mixed methods approach would leverage multiple schools of thought and epistemological perspectives to promote a balanced assessment of big data systems and similar technological advancements.

9.6. Conclusion

With the growing application of big data technologies, there has been an enormous focus on the technology as an independent entity without realising the social contexts in which these technologies are utilised. Yet, as widely argued by IS theories, technologies are often inseparable from social contexts. Uncontested, the recognition of the social realm triggered the wide acceptance of the socio-technical school of thought and other theoretical perspectives that criticise technological determinism. The focus of this study was twofold; first, we raised the question of how the social factors interact with the technical factors in BDA to influence decision-making and institutional performance. Second, we considered how such influences explain the application of BDA in less investigated contexts such as HEIs and developing countries. Generally, we conveyed the BDA socio-technical systems model and examined how it influences decision-making and institutional performance.

Adopting the STS theory, we articulated the social and technical factors of big data systems and explored their role in analytic-driven decision-making and performance in HEIs. Actors and institutional structures represent the BDA social systems. BDA system actors, including the technical and non-technical performers. The technical factors include data scientists responsible for managing data quality. In contrast, the non-technical factors include academic and non-academic employees who are directly or indirectly responsible for observing data security and privacy practices. Institutional structures could denote organisational culture and other operational frameworks within the organisation. This study considered the culture of accepting and adopting technological advancements as the core to creating a data-driven organisation. We have reported the role of organisational culture in shaping BDA teams and that such culture may not directly but could indirectly influence the BDA systems.

The technical subsystem was studied using the STS theory, DeLone and McLean IS success model. According to the STS theory, the technical aspects include the systems and tasks. DeLone and McLean specified the role of system quality in eliciting the system elements. Three features denoted BDA system quality: big data security, privacy, and quality. BDA tasks were developed based on the data lifecycle to include data storage, analysis, and visualisation. Storage tasks also involve collecting big data from multiple sources, while visualisation involves utilising big data. The study examined how social factors influence technical aspects. More specifically, IT staff positively influence big data security and privacy, whereas data scientists, another group of actors, positively impacts big data quality and tasks. Besides, social aspects such as organisational culture did not directly affect the technical aspects of BDA systems. Importantly, organisational culture plays a key role in shaping BDA tasks.

In addition, technical attributes such as system quality positively impact executives' decisions in Saudi HEIs. However, big data security does not influence improving decision-making. As reported in prior studies, improving the decisions of executives directly influences institutional performance. Overall, higher education sectors must recognise the importance of socio-technical factors related to BDA, especially the importance of big data teams, including the technical and non-technical staff. Institutional structures shape big data teams and tasks, which in turn shape system quality, decision-making, and institutional performance outcomes

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Appendix A: Survey English Version

Big Data Analytics Socio-Technical Systems on Strategic Decision Making and Organisational Performance: Case of Saudi Arabian Higher Education.

Consent Form & Information Sheet

My name is Maher Mohammed Aseeri, and I am a Ph. D. candidate at the University of Technology, Sydney. The purpose of this research /online survey is to find how the human and organizational culture factors, along with technology, lead to the successful implementation of big data analytics systems in Saudi Arabian Universities. This development could help improve decision-making by senior management in Saudi universities. The survey takes approximately 8-10 minutes. The researcher believes that there is little or no risk associated with your participation. Your responses will be kept confidential and only used for academic purposes. Participation in this research study is completely voluntary. You have the right to withdraw at any time or refuse to participate entirely. If you agree to be part of the research, data gathered from this survey is to be published in a form that does not identify you.
Please continue answering the survey questions. If you have concerns about the research that you think my supervisor or I can help you with, please feel free to contact me (us) at +61 2 9514 1912. Or via email Maher.M.Aseeri@student.uts.edu.au. My supervisor is Dr. Kyeong Kang.Kyeong.Kang@uts.edu.au.

○ Yes, I Consent

○ No, I Don't Consent

What is your gender?

○ Male

○ Female

○ Prefer not to say

What is your age group?

- ◯ 18-25
- ◯ 26-35
- ◯ 36-45
- ◯ 46 and above

Current Educational level?

- ◯ Diploma
- ◯ Bachelor's Degree
- ◯ Master's Degree
- ◯ Doctoral Degree
- ◯ Others, please specify

What is your Nationality?

- ◯ Saudi
- ◯ Non Saudi - Born in Saudi
- ◯ Non- Saudi

Which university do you work at?

- ◯ Al-Faisal University
- ◯ Al- Qassim University
- ◯ Jazan University
- ◯ Hail University
- ◯ Islamic University In Madinah
- ◯ Immam Mohammed Ibn Saud Islamic University
- ◯ Taibah University
- ◯ Saudi Electronic University
- ◯ Others, please specify

Experience at your University?

- ◯ Less than one year
- ◯ One year
- ◯ 2-3 Years
- ◯ 4-5 Years
- ◯ More than 5 years

What is your current role at university?

- ◯ University Deanship of Information Technology
- ◯ Dean of Information Technology College
- ◯ IT executive level\ IT managers
- ◯ IT Academic Staff
- ◯ programmer- Developer
- ◯ IT Technician/ employee in Information Technology Department

Do you have experience using an information system in data analytics at your university?

- ◯ Yes
- ◯ No

What types of information system do you use for data analytics?

- ◯ Exclusive information system (Top management)
- ◯ Decision support system (senior managers)
- ◯ Management information system (middle managers)
- ◯ Transaction processing system (operational)

What types of analytical tools do you use for data analytics?

- ○ A- Apache Spark on Hadoop
- ○ Apache Cassandra
- ○ SAP business intelligence platforms
- ○ Google Analytics
- ○ Mongo DB
- ○ Others, please specify

What type of decisions could big data analytics support?

- ○ Top management decision support
- ○ Academic decision support
- ○ Financial decision support
- ○ Improving performance decision support

Please rate the degree to which you agree with each statement related to **Tasks (storing big data)** for big data analytics.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
My university has the ability to store very large, unstructured, or fast-moving data such as (data streaming).	○	○	○	○	○
My university has the capability of storing big data from reliable various sources.	○	○	○	○	○
My university has the ability to store multiple big data from (internal and external) sources.	○	○	○	○	○

Please rate the degree to which you agree with each statement related to **Tasks (Analyzing big data).**

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
My university has the ability to analyze big data.	○	○	○	○	○
My university has the ability to analyze big data from internal and external resources.	○	○	○	○	○
My university can analyze big data from reliable various resources.	○	○	○	○	○

Please rate the degree to which you agree with each statement related to Tasks (visualizing analyzed data).

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
My university has the ability to visualize and analyzed big data.	○	○	○	○	○
My university has the ability to visualize analyzed big data from internal and external resources.	○	○	○	○	○
My university has the capability to visualize analyzed data from reliable various resources.	○	○	○	○	○

Please rate the degree to which you agree with each statement related to IT Staff that, Includes (academic and non-academic staff) for big data security.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
IT staff should be encouraged to secure big data.	○	○	○	○	○
In my university, the IT Staff rely on system quality to ensure that big data is secured.	○	○	○	○	○
In my university, the IT staff should be responsible for the security of big data.	○	○	○	○	○

Please select the degree to which you agree with each statement related to IT Staff that Includes (academic and non-academic staff) for big data privacy.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
In my university, IT Staff rely on system to ensure that big data is private.	○	○	○	○	○
In my university, the IT staff should be responsible for the privacy of big data.	○	○	○	○	○
IT staff should have a policy standard for big data privacy.	○	○	○	○	○

People Data scientist please rate the degree to which you agree with each statement related to Data scientists for big data.

Data scientists: A qualified staff who analyzes big data for helping decision-makers to make their decisions based on analyzed data.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
In my university, Data Scientists are important for evaluating big data quality.	○	○	○	○	○
In my university, Data Scientists are crucial for maintaining big data quality.	○	○	○	○	○
In my university, Data Scientists are a vital human factor in storing, analyzing, and visualizing analyzed big data.	○	○	○	○	○

Please rate the degree to which you agree with each statement related to (Accepting big data technological improvements)

Accepting big data technological improvements: Refers to the ability of the university's staff accept big data analytics new technological improvements that include security, privacy, and big data quality.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
My university will accept new innovations such as big data analytics.	○	○	○	○	○
My university will accept big data technological improvements.	○	○	○	○	○
My university will accept technological upgrades for big data analytics.	○	○	○	○	○

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
My university always keens on new changes such as big data analytics technological improvements.	○	○	○	○	○
My university plans to adapt to new technological changes in big data analytics.	○	○	○	○	○
My university would adapt to new technological changes for big data analytics.	○	○	○	○	○

Please select the degree to which you agree with each statement related to (Adapt to new changes) Adapting to new big data technological improvements: Refers to the process of Adapting to new big data analytics new technological improvements that include big data security, privacy, and big data quality.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
My university always keens on new changes such as big data analytics technological improvements.	○	○	○	○	○
My university plans to adapt to new technological changes in big data analytics.	○	○	○	○	○
My university would adapt to new technological changes for big data analytics.	○	○	○	○	○

Please rate the degree to which you agree with each statement related to **system quality** (security of big data)

system quality: Refers to the quality of the system that provides specific functions, in this research, we focus on these functions: Security, privacy, and big data quality.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
Data protection in big data systems is very important for maintaining data security.	○	○	○	○	○
Restricting data access in big data systems is very important for maintaining data security.	○	○	○	○	○
Analyzed data that is used for decision-making should be accessed only by decision-makers.	○	○	○	○	○

Please rate the degree to which you agree with each statement regarding **system quality** (privacy of big data)

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
Big data systems should have controls for data sharing.	○	○	○	○	○
Big data systems should protect information about the personal identity of decision-makers.	○	○	○	○	○
The university should have a policy standard for big data privacy.	○	○	○	○	○

Please rate the degree to which you agree with each statement related to **system quality (quality of big data)**

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The quality of big data is crucial.	○	○	○	○	○
Technological improvements should include Implementing big data system for big data quality.	○	○	○	○	○
The quality of big data is vital for decision making.	○	○	○	○	○

Please select the degree to which you agree with each statement regarding **Improving Decision Making.**

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
Big data analytics systems will improve the effectiveness of decision-making.	○	○	○	○	○
Big data analytics systems will help top management to make their decision faster.	○	○	○	○	○
Big data analytics systems will increase the number of decisions made by top management	○	○	○	○	○
Big data analytics systems will increase the confidence of top management to make decisions based on analyzed data.	○	○	○	○	○

Please select the degree to which you agree with each statement regarding Improving Organization's Performance (KPI).
KPI (**Key Performance Indicators):** Refers to the process of measuring your progress toward intended objectives.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The number of decisions made by analyzed data are increased for better performance.	○	○	○	○	○
Big data analytics saves the costs of hiring experts for making decisions.	○	○	○	○	○
BA bigdata analytics system will help top management tmprove scientific research and development.	○	○	○	○	○
Big data analytics will create business value.	○	○	○	○	○
Big data analytics will improve the overall university's performance.	○	○	○	○	○

Appendix B: Survey Arabic Version

العوامل البشرية والثقافة التنظيمية لدعم تحليلات البيانات الضخمة في التعليم العالي السعودي

نموذج الموافقة وورقة المعلومات

الغرض من هذا البحث / المسح .اسمي ماهر محمد عسيري، وأنا مرشح لنيل درجة الدكتوراه في الجامعة التكنولوجية في سيدني عبر الإنترنت هو معرفة كيف تؤدي عوامل الثقافة البشرية والتنظيمية ، إلى جانب التكنولوجيا ، إلى التنفيذ الناجح لأنظمة تحليل ويمكن أن يساعد هذا التطور في تحسين عملية صنع القرار من قبل الإدارة العليا في .البيانات الضخمة في الجامعات السعودية يعتقد الباحث أن هناك مخاطر قليلة أو معدومة مرتبطة .يستغرق الاستطلاع حوالي 8-10 دقائق .الجامعات السعودية المشاركة في هذه الدراسة البحثية طوعية .سيتم الحفاظ على سرية ردودك واستخدامها فقط للأغراض الأكاديمية .بمشاركتك إذا كنت توافق على أن تكون جزءا من البحث ، نشر .لديك الحق في الانسحاب في أي وقت أو رفض المشاركة بالكامل .تماما .البيانات التي تم جمعها من هذا الاستطلاع في شكل لا يحدد هويتك

إذا كانت لديك مخاوف بشأن البحث الذي تعتقد أنه يمكنني مساعدتك فيه أو مشرفي .الرجاء استمر في الإجابة على أسئلة الاستطلاع أو عبر البريد الإلكتروني .، فلا تتردد في الاتصال بي (لنا) على +61 2 9514 1912
Maher.M.Aseeri@student.uts.edu.au. مشرفي هو الدكتور كيونغ Kang.Kyeong.Kang@uts.edu.au.

نعم، أوافق ○

لا، أنا لا أوافق ○

ما هو جنسك؟

ذكر ○

أنثى ○

يفضل ألا يقول ○

ما هي فئتك العمرية؟

18-25 ○

○ 26-35

○ 36-45

○ 46 وما فوق

المستوى التعليمي الحالي؟

○ دبلوم

○ درجة البكالوريوس

○ درجة الماجستير

○ درجة الدكتوراه

○ آخرى، يرجى التحديد

ما هي جنسيتك؟

○ سعودي

○ غير سعودي - ولد في السعودية

○ غير سعودي

ما هي الجامعة التي تعمل فيها؟

○ جامعة الفيصل

○ جامعة القصيم

○ جامعة جازان

○ جامعة حائل

○ الجامعة الإسلامية بالمدينة المنورة

جامعة إمام محمد بن سعود الإسلامية ◯

جامعة طيبة ◯

الجامعة السعودية الالكترونية ◯

آخرى، يرجى التحديد ◯

سنوات الخبرة في جامعتك؟

أقل من سنة واحدة ◯

سنة واحدة ◯

سنوات 2-3 ◯

سنوات 4-5 ◯

أكثر من 5 سنوات ◯

ما هي وظيفتك الحالية في الجامعة؟

عمادة تقنية المعلومات بالجامعة ◯

عميد كلية تقنية المعلومات ◯

المستوى التنفيذي لتكنولوجيا المعلومات / مديري تكنولوجيا المعلومات ◯

أعضاء هيئة التدريس في تكنولوجيا المعلومات ◯

مبرمج - مطور ◯

فني تكنولوجيا المعلومات / موظف في قسم تقنية المعلومات ◯

هل لديك خبرة في استخدام نظام المعلومات في تحليل البيانات في جامعتك؟

نعم ◯

لا ◯

ما هي أنواع أنظمة المعلومات التي تستخدمها لتحليل البيانات؟

نظام معلومات حصري (الإدارة العليا)

نظام دعم القرار (كبار المديرين)

نظام المعلومات الإدارية (المدراء المتوسطون)

نظام معالجة المعاملات (التشغيلي)

ما هي أنواع الأدوات التحليلية التي تستخدمها لتحليل البيانات؟

أ- أباتشي سبارك على هادوب

أباتشي كاساندرا

SAP منصات ذكاء الأعمال

تحليلات جوجل

DB مونغو

آخرى، يرجى التحديد

ما نوع القرارات التي يمكن أن تدعمها تحليلات البيانات الضخمة؟

دعم قرار الإدارة العليا

دعم القرار الأكاديمي

دعم القرارات المالية

تحسين دعم قرارات الأداء

.يرجى تقييم درجة موافقتك على كل عبارة تتعلق **بالمهام (تخزين البيانات الضخمة)** لتحليلات البيانات الضخمة

	أوافق بشدة	أوافق إلى حد ما	لا توافق ولا تختلف	لا أوافق إلى حد ما	لا أوافق بشدة
تتمتع جامعتي بالقدرة على تخزين بيانات كبيرة جدا أو					

غير منظمة أو سريعة الحركة مثل (تدفق البيانات).					
تتمتع جامعتي بالقدرة على تخزين البيانات الضخمة من مصادر مختلفة موثوقة.					
جامعتي لديها القدرة على تخزين بيانات كبيرة متعددة من مصادر (داخلية وخارجية).					

يرجى تقييم درجة موافقتك على كل عبارة تتعلق **بالمهام (تحليل البيانات الضخمة).**

	أوافق بشدة	أوافق إلى حد ما	لا توافق ولا تختلف	لا أوافق إلى حد ما	لا أوافق بشدة
جامعتي لديها القدرة على تحليل البيانات الضخمة.					
جامعتي لديها القدرة على تحليل البيانات الضخمة من الموارد الداخلية والخارجية.					
تتمتع جامعتي بالقدرة على تحليل البيانات الضخمة من موارد مختلفة موثوقة.					

يرجى تقييم درجة موافقتك على كل عبارة تتعلق بالمهام (تصور البيانات التي تم تحليلها).

	أوافق بشدة	أوافق إلى حد ما	لا توافق ولا تختلف	لا أوافق إلى حد ما	لا أوافق بشدة
جامعتي لديها القدرة على تصور البيانات الضخمة التي تم تحليلها.					
تتمتع جامعتي بالقدرة على تصور البيانات الضخمة التي تم تحليلها من الموارد الداخلية والخارجية.					
تتمتع جامعتي بالقدرة على تصور البيانات التي تم					

تحليلها من موارد مختلفة موثوقة.

يرجى تقييم الدرجة التي توافق بها على كل بيان يتعلق بموظفي تكنولوجيا المعلومات يتضمن (أعضاء هيئة التدريس وغير الأكاديميين) لأمن البيانات الضخمة.

	أوافق بشدة	أوافق إلى حد ما	لا توافق ولا تختلف	لا أوافق إلى حد ما	لا أوافق بشدة
ينبغي تشجيع موظفي تكنولوجيا المعلومات على تأمين البيانات الضخمة.	○	○	○	○	○
في جامعتي ، يعتمد موظفو تكنولوجيا المعلومات على جودة النظام لضمان تأمين البيانات الضخمة.	○	○	○	○	○
في جامعتي ، يجب أن يكون موظفو تكنولوجيا المعلومات مسؤولين عن أمن البيانات الضخمة.	○	○	○	○	○

يرجى تحديد الدرجة التي توافق عليها مع كل بيان يتعلق بموظفي تكنولوجيا المعلومات يتضمن (أعضاء هيئة التدريس وغير الأكاديميين) لخصوصية البيانات الضخمة.

	أوافق بشدة	أوافق إلى حد ما	لا توافق ولا تختلف	لا أوافق إلى حد ما	لا أوافق بشدة
في جامعتي ، يعتمد موظفو تكنولوجيا المعلومات على النظام لضمان خصوصية البيانات الضخمة.	○	○	○	○	○
في جامعتي ، يجب أن يكون موظفو تكنولوجيا المعلومات مسؤولين عن خصوصية البيانات الضخمة.	○	○	○	○	○
يجب أن يكون لدى موظفي تكنولوجيا المعلومات معيار سياسة لخصوصية البيانات الضخمة.	○	○	○	○	○

.يرجى تقييم درجة موافقتك على كل عبارة تتعلق بعلماء البيانات للبيانات الضخمة

علماء البيانات: فريق عمل مؤهل يقوم بتحليل البيانات الضخمة لمساعدة صناع القرار على اتخاذ قراراتهم بناء على البيانات التي تم تحليلها.

	أوافق بشدة	أوافق إلى حد ما	لا توافق ولا تختلف	لا أوافق إلى حد ما	لا أوافق بشدة
في جامعتي ، علماء البيانات مهمون لتقييم جودة البيانات الضخمة.					
في جامعتي ، يعد علماء البيانات أمرا بالغ الأهمية للحفاظ على جودة البيانات الضخمة.					
في جامعتي ، يعد علماء البيانات عاملا بشريا حيويا في تخزين وتحليل وتصور البيانات الضخمة التي تم تحليلها.					

يرجى تقييم درجة موافقتك على كل عبارة تتعلق ب (قبول التحسينات التكنولوجية للبيانات الضخمة)

قبول التحسينات التكنولوجية للبيانات الضخمة: يشير إلى قدرة موظفي الجامعة على قبول تحليلات البيانات الضخمة والتحسينات التكنولوجية الجديدة التي تشمل الأمن والخصوصية وجودة البيانات الضخمة.

	أوافق بشدة	أوافق إلى حد ما	لا توافق ولا تختلف	لا أوافق إلى حد ما	لا أوافق بشدة
ستقبل جامعتي ابتكارات جديدة مثل تحليلات البيانات الضخمة.					
ستقبل جامعتي التحسينات التكنولوجية للبيانات الضخمة.					
ستقبل جامعتي الترقيات التكنولوجية لتحليلات البيانات الضخمة.					

يرجى تحديد الدرجة التي توافق بها على كل عبارة تتعلق ب (التكيف مع التغييرات الجديدة)

التكيف مع التحسينات التكنولوجية الجديدة للبيانات الضخمة: يشير إلى عملية التكيف مع تحليلات البيانات الضخمة الجديدة التحسينات التكنولوجية الجديدة التي تشمل أمن البيانات الضخمة والخصوصية وجودة البيانات الضخمة.

	أوافق بشدة	أوافق إلى حد ما	لا توافق ولا تختلف	لا أوافق إلى حد ما	لا أوافق بشدة

حرصت جامعتي دائما على التغييرات الجديدة مثل التحسينات التكنولوجية لتحليلات البيانات الضخمة.	○	○	○	○	○
تخطط جامعتي للتكيف مع التغيرات التكنولوجية الجديدة في تحليلات البيانات الضخمة.	○	○	○	○	○
سوف تتكيف جامعتي مع التغيرات التكنولوجية الجديدة لتحليلات البيانات الضخمة.	○	○	○	○	○

يرجى تقييم درجة موافقتك على كل بيان يتعلق **بجودة النظام (**أمان البيانات الضخمة

جودة النظام: يشير إلى جودة النظام الذي يوفر وظائف محددة، في هذا البحث، نركز على هذه الوظائف: الأمان، والخصوصية، وجودة البيانات الضخمة.

	أوافق بشدة	أوافق إلى حد ما	لا توافق ولا تختلف	لا أوافق إلى حد ما	لا أوافق بشدة
تعد حماية البيانات في أنظمة البيانات الضخمة مهمة جدا للحفاظ على أمان البيانات.	○	○	○	○	○
يعد تقييد الوصول إلى البيانات في أنظمة البيانات الضخمة أمرا مهما للغاية للحفاظ على أمان البيانات.	○	○	○	○	○
يجب الوصول إلى البيانات التي تم تحليلها والتي تستخدم لصنع القرار فقط من قبل صانعي القرار.	○	○	○	○	○

خصوصية البيانات الضخمة)يرجى تقييم درجة موافقتك على كل بيان فيما يتعلق **بجودة النظام**

	أوافق بشدة	أوافق إلى حد ما	لا توافق ولا تختلف	لا أوافق إلى حد ما	لا أوافق بشدة

يجب أن تحتوي أنظمة البيانات الضخمة على عناصر تحكم لمشاركة البيانات.	○	○	○	○	○
يجب أن تحمي أنظمة البيانات الضخمة المعلومات المتعلقة بالهوية الشخصية لصانعي القرار.	○	○	○	○	○
يجب أن يكون لدى الجامعة معيار سياسة لخصوصية البيانات الضخمة.	○	○	○	○	○

(جودة البيانات الضخمة)يرجى تقييم درجة موافقتك على كل عبارة تتعلق **بجودة النظام**

	أوافق بشدة	أوافق إلى حد ما	لا توافق ولا تختلف	لا أوافق إلى حد ما	لا أوافق بشدة
جودة البيانات الضخمة أمر بالغ الأهمية.	○	○	○	○	○
يجب أن تشمل التحسينات التكنولوجية تنفيذ نظام البيانات الضخمة لجودة البيانات الضخمة.	○	○	○	○	○
تعد جودة البيانات الضخمة أمرا حيويا لاتخاذ القرارات.	○	○	○	○	○

.يرجى تحديد الدرجة التي توافق بها على كل بيان يتعلق **بتحسين عملية صنع القرار**

	أوافق بشدة	أوافق إلى حد ما	لا توافق ولا تختلف	لا أوافق إلى حد ما	لا أوافق بشدة
سيحسن نظام تحليل البيانات الضخمة من فعالية صنع القرار.	○	○	○	○	○
سيساعد نظام تحليلات البيانات الضخمة الإدارة العليا على اتخاذ قرارها بشكل أسرع.	○	○	○	○	○
سيزيد نظام تحليل البيانات الضخمة من عدد القرارات	○	○	○	○	○

التي تتخذها الإدارة العليا					
سيزيد نظام تحليلات البيانات الضخمة من ثقة الإدارة العليا في اتخاذ القرارات بناء على البيانات التي تم تحليلها.	○	○	○	○	○

(KPI) يرجى تحديد الدرجة التي توافق بها على كل بيان يتعلق بتحسين أداء المنظمة.
KPI **(مؤشرات الأداء الرئيسية):** يشير إلى عملية قياس تقدمك نحو الأهداف المقصودة.

	أوافق بشدة	أوافق إلى حد ما	لا توافق ولا تختلف	لا أوافق إلى حد ما	لا أوافق بشدة
يتم زيادة عدد القرارات التي تتخذها البيانات التي تم تحليلها للحصول على أداء أفضل.	○	○	○	○	○
توفر تحليلات البيانات الضخمة تكاليف توظيف الخبراء لاتخاذ القرارات.	○	○	○	○	○
سيساعد نظام تحليل البيانات الضخمة الإدارة العليا على تحسين البحث العلمي والتطوير.	○	○	○	○	○
ستخلق تحليلات البيانات الضخمة قيمة تجارية.	○	○	○	○	○
ستعمل تحليلات البيانات الضخمة على تحسين الأداء العام للجامعة.	○	○	○	○	○

Appendix C: Interview Questions English Version

Interview Questions

Interview Questions (Dean of Information Technology and distance learning / IT Managers)

INTRODUCTION FOR BIG DATA ANALYTIC

Big data analytics has become crucial for gaining a competitive advantage over others. However, recent research has focused on the technological aspect while ignoring the importance of human and cultural factors and technology to gain advantage of big data analytics in educational sectors. These factors could lead to improve decision-making by top management in Saudi-selected universities. Besides, in this interview, I would like to discuss these factors and how they can improve the current process or state of big data analytics in Saudi higher educational firms.

In this paragraph, I would like to explain the term System quality. System quality is one dimension of Delone and Maclean's success information model for the system's overall quality. In our study, system quality is big data analytics system that allows access, analysis, security, privacy and quality of big data.

Good morning sir, and thanks for this opportunity. I will begin with big data analytics performers, including IT academic and non-academic staff.

Constructs	Interview Question
People and system quality	a) What would be the role of (IT staff) in big data (security), (privacy) b) What would be the role of (Data scientist) in big data (quality)?
Data scientists and big data tasks	a) Do you think storing, analysing, and visualising would be the role of data scientists? *If yes how*? *If not why?*

Organisational culture and big data system	a) Would your university accept and adapt to new technological improvements for big data (security), (privacy), and (quality)? *If yes, how will it enable these? If no, why do you think it will not?*
Organisational culture and big data performers	a) Would accept and adapt to new technological improvements affect the roles of (IT staff) (data scientists) in big data? *If yes, how? If no, why not?*
Organisational culture and big data Tasks	a) Would adapting to new technological improvements enable (storing) (analysing) (visualising) big data? If yes, how? If no, why not?
Big data system and decision making	a) Does **(privacy)** in big data analytics system would help to improve the decision-making of top managers? *If yes, how? If no, why not?* b) Does **(security)** in big data analytics system help improve top managers' decision-making? *If yes, how? If no, why not?* c) Do you think big data quality will improve the decision-making by top managers *If yes, how? If no, why not?*
Big data tasks and decision making	a) Do you think (storing) (analysing), (and visualising) big data improves the decision-making by top managers? If yes, how? If no, why not?
Big data-enabled decision making	a) Would big data analytics support your decision-making needs? If yes, how? If no, why not? b) Do you think big data security, privacy, and quality will improve the effectiveness of your decisions? If yes, how? If no, why not?
Enhancing organisational performance	a) Do you think improving senior managers' decision-making will improve your organisation's performance? If yes, how? If no, why not? b) Which decisions do you think will improve your university performance? In Finance?Academic? Technological? If yes, how? If no, why not?

Thanks for your valuable time and your patience.

Would you like to add any comments that could help in my current project?

Is there anyone else you think I should be talking to?

Someone who could add another important perspective on this topic?

Should I contact them directly and can I mention that you recommended that I talk to them?

End/Thanks

Appendix D: Interview Questions Arabic Version

أسئلة المقابلة

أسئلة المقابلة الخاصة سعادة مدير الجامعة / موظفي الإدارة العليا الذين يشاركون في صنع القرار.

مقدمة عن تحليل البيانات الضخمة

أصبحت عملية تحليل البيانات الضخمة مهمة للغاية في الوقت الحاضر لاكتساب ميزة تنافسية على الآخرين، حيث ركزت الأبحاث الحديثة على الجانب التكنولوجي مع تجاهل أهمية العوامل البشرية والثقافية إلى جانب التكنولوجيا لاكتساب مزايا تحليل البيانات الضخمة في قطاعات التعليم؛ هذه العوامل قد تساعد على تحسين صنع القرار من قبل الادارة العليا في الجامعات السعودية.

في هذه المقابلة، أود مناقشة هذه العوامل وكيف يمكنهم تحسين العملية الحالية أو حال تحليل البيانات الضخمة في قطاعات التعليم العالي في السعودية.

أسعد الله أوقاتكم سيدي وأشكركم لمنحي هذه الفرصة؛ سأبدأ بالمهام المدرجة في تحليل البيانات الضخمة والتي تتضمن ثلاث خطوات أولية: تخزين البيانات الضخمة من مصادر خارجية وداخلية، وتحليلها بناءً على احتياجات المنظمة، ثم عرضها لصناع القرار لإستنتاج معنى من البيانات ولتحسين صنع القرارات.
في الفقرة التالية، أود أن أعرض بإيجاز المصطلحات التكنولوجية ذات الصلة وتعاريفها.

نظم المعلومات: مجموعة متكاملة من المكونات لجمع البيانات وتخزينها ومعالجتها لتوفير المعلومات والمعرفة.

في هذه الفقرة، أود توضيح مفهوم جودة النظام حيث تعد جودة النظام أحد أبعاد نموذج Delone وMaclean لنجاح نظم المعلومات وللحصول على الجودة الشاملة للنظام؛ وفي دراستنا هذه، تعد جودة النظام عبارة عن نظام لتحليل البيانات الضخمة والذي يسمح بالوصول إلى البيانات الضخمة وتخزينها وتحليلها وتأمينها والحفاظ على خصوصيتها وجودة البيانات الضخمة.

نموذج البحث	**أسئلة المقابلة**
المهام	***تخزين* البيانات الضخمة** - هل تستورد الجامعة البيانات من مصادر مختلفة (بيانات داخلية وخارجية) لتخزينها؟ ما هو نوع المصادر الخارجية التي تفضل استيراد البيانات الكبيرة؟ البيانات المتدفقة؟ هل هذه البيانات المستوردة موثوقة؟ هل تعتقد أن القدرة على استيراد البيانات الضخمة من مختلف الموارد تساهم في أمن البيانات والخصوصية والجودة؟ كيف؟
	***تحليل* البيانات الضخمة**

	- هل تقوم الجامعة بتحليل البيانات المستوردة من مصادر مختلفة؟ إذا كان الجواب نعم، كيف؟ إذا كان لا، لماذا لا تقوم الجامعة بتحليل البيانات؟ هل تعتقد أن القدرة على تحليل البيانات الضخمة من مختلف الموارد تساهم في أمن البيانات والخصوصية والجودة؟ كيف؟
	***التصور*(عرض) البيانات المحللة** - هل تعرض الجامعة البيانات التي تم تحليلها من مصادر مختلفة؟ إذا كان الجواب نعم، ما هي الأدوات التي تستخدمها؟ في أي أشكال تصور البيانات المحللة؟ - هل تساهم القدرة على تصور(عرض) البيانات المحللة في تحسين نوعية النظم التحليلية للبيانات الضخمة؟ كيف؟
جودة النظام	***الخصوصيه*(خصوصية البيانات الضخة)** - ما هي وجهات نظركم حول الخصوصية في تحليلات البيانات الضخمة؟ - ما هي الوظائف التي ينبغي أن يوفرها النظام لضمان خصوصية البيانات؟ - هل ضمان الخصوصية في نظام تحليل البيانات الضخمة يساعد على تحسين عملية اتخاذ القرارات لكبار المديرين؟ كيف؟
	***الامن* أمن البيانات الضخمة** - ما هي وجهات نظركم حول أمان تحليلات البيانات الكبيرة؟ - ما هي الوظائف التي ينبغي أن يوفرها النظام لضمان أمن البيانات؟ مثلاً تقييد الوصول للبيانات الضخمة من قبل صانعي القرار فقط؟ - هل يؤدي ضمان الأمن في نظام تحليل البيانات الضخمة دوراً في تحسين عملية اتخاذ القرارات لكبار المديرين؟ كيف؟
	جودة البيانات الكبيرة- - ما هي وجهات نظركم حول جودة البيانات الضخمة؟ - ما هي الوظائف التي ينبغي أن يوفرها النظام لضمان جودة البيانات في نظم تحليل البيانات الضخمة؟ - هل يساعد ضمان جودة البيانات في نظام تحليل البيانات الضخمة في تحسين عملية اتخاذ القرارات لكبار المديرين؟ كيف؟
المسؤولين عن تحليل البيانات الضخمة	***موظفو تقنية المعلومات (الأكاديميين وغير الأكاديميين)*** هل تعتقد أن أعضاء هيئة التدريس وغير الأكاديميين في مجال تكنولوجيا المعلومات يجب أن يكونوا مسؤولين عن أمن البيانات التي تم تحليلها؟ لماذا؟ هل سيحسن اتخاذ القرار؟ - ما هو دور الموظفين الأكاديميين وغير الأكاديميين في تأمين البيانات المحللة؟ هل تعتقد أن أعضاء هيئة التدريس وغير الأكاديميين في مجال تكنولوجيا المعلومات يجب أن يكونوا مسؤولين عن خصوصية البيانات التي تم تحليلها؟ لماذا؟ سيحسن اتخاذ القرار؟
	علماء البيانات -لماذا من المهم أن يكون هناك علماء بيانات في الجامعة؟ ما هو دورهم فيما يتعلق بالبيانات الضخمة، بشكل عام؟ هل تعتقد بأن علماء البيانات لهم دور مهم في ضمان جودة البيانات الضخمة؟

	- هل تعتقد أن جودة البيانات المحللة تؤدي تحسين القرارات لكبار المديرين؟ كيف؟
الثقافة التنظيمية	***القدرة على قبول التغيير*** - هل يمكنك أن تصف ثقافة منظمتك فيما يتعلق بقبول التقنيات أو العمليات الجديدة؟ هل يمكن أن تعطي مثالاً على التغيرات التكنولوجية الجديدة السابقة التي تم قبولها داخل جامعتك؟ -هل يمكنك أن تصف الثقافة السائدة في جامعتك فيما يتعلق بقبول التحسينات التكنولوجية التي تشمل الأمن والخصوصية؟ -هل تصف الثقافة في الجامعة فيما يتعلق بقبول التحسينات التكنولوجية الجديدة لجودة البيانات الكبيرة؟
	القدرة على التكيف مع التغييرات الجديدة - هل يمكنك أن تصف ثقافة منظمتك فيما يتعلق بالتكيف مع التكنولوجية أو العمليات الجديدة؟ - هل تعتقد أن التكيف مع التحسينات التكنولوجية الجديدة سيحسن أمن البيانات الضخمة والخصوصية والجودة؟ إذا كانت الإجابة بنعم، كيف سيمكن هذه؟ إذا كان لا، لماذا تعتقد أنه لن يؤدي إلى أي تحسن؟
تحسين عملية صنع القرار	- ما هي القرارات التي تتخذها كا رئيس الجامعة - ما هي التقنيات التي تستخدمها لدعم احتياجات اتخاذ القرار؟ - هل تعتقد أن تحليلات البيانات الضخمة ستدعم احتياجاتك في صنع القرار؟ - فيما يتعلق بجودة أنظمة تحليل البيانات الضخمة، هل تعتقد أن أمن البيانات الكبيرة والخصوصية والجودة سوف تحسن فعالية قراراتك؟
تعزيز أداء المؤسسة	هل تعتقد أن تحسين عملية اتخاذ القرارات لكبار المديرين سيحسن أداء مؤسستك؟ كيف؟ - في أي مجال تعتقد أن تحسين عملية صنع القرار سيساعد على تحسين أداء المنظمات؟ في مجال التمويل؟ الاكاديميه؟ التكنولوجيه؟ كيف؟

شكرا على وقتكم الثمين وسعة صدركم

هل ترغب في إضافة أي ملاحظات يمكنها أن تساعد في مشروعي الحالي؟ هل هناك أي شخص آخر تعتقد أنني يجب علي التحدث إليه بالخصوص؟ هل هناك شخص يمكنه أن يضيف وجهة نظر أخرى مهمة حول هذا الموضوع؟ هل يجب علي الاتصال بهم مباشرة وهل يمكنني أن أذكر أنك أوصيت بأن أتحدث إليهم؟

انتهى، مع الشكر

Appendix E: Information Sheet& Consent Form for Survey English Version

Information Sheet And Consent Form For Online Surveys

ETH19-4262: Big Data Analytics Socio-Technical Systems on Strategic Decision Making and Organisational Performance: Case of Saudi Arabian Higher Education.

The purpose of this research/online survey is to find how human and cultural factors along with technology as a mediator lead to develop success implementation of big data analytics in Saudi Higher education. Besides, big data analytics can help top management in selected universities to make an effective decision making as well as improve organisational performance.

You have been invited to participate because you are IT staff, working in one of selected Saudi Arabian universities and have related knowledge.

Who is conducting this research?

My name is *Maher Mohammed Asseri,* and I am a Ph.D. Student at UTS. My supervisor is *Kyeong kang.*

Inclusion/Exclusion Criteria

Before you decide to participate in this research study, we need to ensure that it is ok for you to take part. Inclusion of this online survey will IT staff, Information security, Data scientist if applicable, and System

Admin. Exclusion of this online survey will be administrative staff in Saudi Arabian Selected universities.

Do I have to take part in this research study?

Participation in this study is voluntary. It is completely up to you whether or not you decide to take part. If you decide to participate, I will invite you to you will be asked to answer some questions in the questionnaire. The survey will take approximately 15-20 minutes.

Read the information carefully (ask questions if necessary);

- *Complete an online questionnaire.*

You can change your mind at any time and stop completing the surveys without consequences.

Are there any risks/inconvenience?

We don't expect this questionnaire to cause any harm or discomfort, however if you experience feelings of distress as a result of participation in this study you can let the researcher know and they will provide you with assistance.

What will happen to information about me?

Access to the online questionnaire is via Qualtrics online survey Submission of the online questionnaire/s is an indication of your consent. By clicking the on invitation links or clicking on No I do not concern button provided in information and consent form of online survey, you consent to the research team collecting and using personal information about you for the research project. All this information will be treated confidentially. Data records will be stored in the following format: voice recording and transcripts. Data will be saved on UTS OneDrive, a backup copy will be saved and password protected in Cloud store, the university cloud storage system, and UTS data management system Stash". Your information will only be used for the purpose of this research project and we would like to store your information for future use in research projects that are an extension of this research project. In all instances your information will be treated confidentially. *It* will only be disclosed with your permission, except as required by law.

What if I have concerns or a complaint?

If you have concerns about the research that you think I or my supervisor can help you with, please feel free to contact me Maher Mohammed Aseeri at (Maher.m.aseeri@student.uts.edu.au) ; Ph:

+61); *+966* or my Principal Supervisor – Dr. Kyeong kang, at

Kyeong.Kang@uts.edu.au; +61 2 95141912) or my local supervisor for data collection in Saudi Arabia Othman M. Asiry at(Asiry@Uj.edu.sa) ; Ph: +966

If you would like to talk to someone who is not connected with the research, you may contact the Research Ethics Officer on 02 9514 9772 or Research.ethics@uts.edu.au and quote this number ETH194262.

Appendix F: Information Sheet& Consent Form for Survey Arabic Version

ورقة معلومات واستمارة موافقة على المشاركة في استبيان عبر الإنترنت

العوامل البشرية والثقافة التنظيمية لدعم تحليلات البيانات الضخمة في التعليم العالي السعودي ETH19-4262:

ما هو موضوع البحث؟
الغرض من هذا البحث/الدراسة التي يجريها الباحث عبر الإنترنت هو معرفة كيف يمكن للعوامل البشرية والثقافية إلى جانب استخدام التكنولوجيا كوسيط أن تؤدي إلى تطوير تطبيق تحليل البيانات الضخمة بنجاح في قطاع التعليم العالي السعودي؛ بالإضافة إلى أن تحليل البيانات الضخمة يمكنها أن تساعد الإدارة العليا في جامعات مختارة على اتخاذ قرارات فعالة وتحسين أداء المؤسسة.
وتمت دعوتك للمشاركة في هذه الدراسة لأنك تعمل في مجال تكنولوجيا المعلومات في إحدى الجامعات السعودية المختارة ولديك معرفة ذات علاقة بموضوع البحث.

من يقوم بالبحث؟
اسمي ماهر محمد العسيري وأنا طالب في جامعة سيدني للتكنولوجيا) UTS(ومشرفي الرئيسي هو د .كيونغ كانغ.

معايير الإشراك والاستبعاد
قبل أن تقرر المشاركة في هذه الدراسة البحثية، نحتاج إلى التأكد من أنه لا مشكلة لديك من المشاركة، سيشمل هذا الاستبيان الالكتروني مشاركة موظفي تكنولوجيا المعلومات وأمن المعلومات وعالم البيانات إن أمكن ومسؤولي النظام، وسيستبعد الكادر الإداري في الجامعات السعودية المختارة.

هل يجب على المشاركة في البحث؟
المشاركة في هذه الدراسة طوعية والأمر متروك لك تمامًا سواء قررت المشاركة أم لا؛ وإذا قررت المشاركة، سأدعوك للإجابة على بعض الأسئلة في الاستبيان حيث سيستغرق ذلك حوالي 15-20 دقيقة، لذا:

- قم بقراءة المعلومات بعناية) يمكنك طرح أسئلة إن لزم الأمر(؛
- أكمل الاستبيان الالكتروني

بإمكانك تغيير رأيك في أي وقت والتوقف عن الإجابة عن أسئلة الاستبيان دون عواقب.

هل هناك أي خطر أو إزعاج قد ينجم عن المشاركة في الاستبانة؟

لا نتوقع أن يتسبب هذا الاستبيان في أي ضرر أو إزعاج، ولكن إذا شعرت بالضيق أو عدم الارتياح نتيجة للمشاركة في هذه الدراسة، فيمكنك إخبار الباحث وستقدم لك المساعدة.

ماذا سيحدث للمعلومات الخاصة بي؟

إن الدخول إلى هذا الاستبيان الالكتروني يتم من خلال التقديم إلى Qualtrics online survey والذي يعد مؤشراً على موافقتك، وممن خلال النقر فوق ارتباطات الدعوة)invitation links(أو النقر فوق" لا، أنا لست مهتم اً بالمشاركة" الموجود في ورقة المعلومات والموافقة على الاستبيان الالكتروني، فإنك توافق على قيام فريق البحث بجمع واستخدام معلوماتك الشخصية لصالح مشروع البحث.

وسيتم التعامل مع كل هذه المعلومات بسرية تامة، كما سيتم تخزين سجلات البيانات بالكيفية التالية: التسجيل الصوتي والنصوص حيث سيتم حفظ البيانات على *UTS OneDrive*، وسيتم حفظ نسخة احتياطية وحماية كلمة المرور في متجر *Cloud*، ونظام التخزين السحابي الجامعي إلى جانب نظام إدارة بيانات *UTS Stash*"؛ ولن يتم استخدام معلوماتك إلا لغرض هذا المشروع البحثي، ونود تخزين معلوماتك لاستخدامها في المستقبل في المشروعات البحثية التي تعد امتدادًا لهذا المشروع البحثي؛ مع التأكيد على أنه في جميع الحالات، سيتم التعامل مع معلوماتك بسرية تامة و سيتم الكشف عنها فقط بعد الحصول على إذ ن منك، باستثناء ما يقتضيه القانون.

ماذا إن كان لدي مخاوف أو شكوى؟

إذا كانت لديك مخاوف بشأن البحث وتعتقد أنه يمكنني أو يمكن للمشرفين مساعدتك، فلا تتردد في الاتصال بي ماهر محمد العسيري على *(Maher.m.aseeri@student.uts.edu.au)* ؛ *Ph: +61* *)* ؛ 966+ أو المشرف الرئيسي د .كيونغ كانغ عبر (Kyeong.Kang@uts.edu.au ؛ 2 95141912 61+ ؛ 6 2 95141827) أو المشرف المحلي الخاص بي لجمع البيانات في المملكة العربية السعودية عثمان محمد العسيري عبر (Asiry@Uj.edu.sa؛ Ph: +966

وإذا كنت ترغب في التحدث إلى شخص ليس له علاقة بالبحث، فيمكنك الاتصال بمسؤول أخلاقيات البحث على 02 9514 9772 أو Research.ethics@uts.edu.au واقتبس هذا الرقم) ETH19-4642

Appendix G: Information Sheet& Consent Form for Interviews English

Participant Information Sheet
ETH19-4262: Human and Cultural Factors for Supporting Big Data Analytics in Higher Education Sectors: A Study of Saudi Arabian Universities.

WHO IS DOING THE RESEARCH?

My name is Maher Mohammed Aseeri and I am a student at UTS. (My Principal Supervisor is Dr. Kyeong Kang and my Co-supervisor is Dr. Daniel Chandran)

WHAT IS THIS RESEARCH ABOUT?

This research is to find out the effect of human and cultural factors along with the technology that support big data analytics for making an effective decision making by top management and improving organization's performance in Saudi Arabian selected universities.

WHY HAVE I BEEN ASKED?

You have been invited to participate in this study because *you are Dean of information technology and distance learning / Dean of IT school / Head of IT Department, working at one of Saudi selected universities, and have related knowledge.*

IF I SAY YES, WHAT WILL IT INVOLVE?

If you decide to participate, I will invite you to *participate in 55 minutes - 1 hour semi-structured interview, will be audio recorded and transcribed as well as you will be observed during the interview by the researcher.*

ARE THERE ANY RISKS/INCONVENIENCE?

This research has no risks during the interview because this study has been carefully designed by the researcher. However, it is possible that you may face some inconvenient because the duration of interview is 55 minutes – 1 hour and the interview will be recorded by two audio recording devices.

DO I HAVE TO SAY YES?

Participation in this study is voluntary. It is completely up to you whether or not you decide to take part.

WHAT WILL HAPPEN IF I SAY NO?

If you decide not to participate, you have the right to refuse or withdraw your participation at any stage of this interview and this will not affect your job or organizational affiliation. If you wish to withdraw from the study once it has started, you can do so at any time without having to give a reason, by contacting *Maher Mohammed Aseeri at (Maher.m.aseeri@student.uts.edu.au) ; Ph: +61*[redacted]*); +966*[redacted]

If you withdraw from the study, however, it may not be possible to withdraw your data from the study results if these have already had your identifying details removed.

If you decide to leave the research project, we will not collect additional personal information from you, although, personal information already collected will be retained to ensure that the results of the research project can be measured properly and to comply with law. You should be aware that data collected up to the time you withdraw will form part of the research project results. If you do not want them to do this, you must tell them before you join the research project.

CONFIDENTIALITY

By signing the consent form you consent to the research team collecting and using personal information about you for the research project. All this information will be treated confidentially. *Data records will be stored in the following format: voice recording and transcripts. Data will be saved on UTS OneDrive, a backup copy will be saved and password protected through university cloud storage system as well as UTS data management system Stash".* Your information will only be used for the purpose of this research project and we would like to store your information for future use in research projects that are an extension of this research project. In all instances your information will be treated confidentially.

WHAT IF I HAVE CONCERNS OR A COMPLAINT?

If you have concerns about the research that you think I or my supervisors can help you with, please feel free to contact me Maher Mohammed Aseeri at (Maher.m.aseeri@student.uts.edu.au) ; Ph: +61[redacted]); *+966*[redacted] or my Principal Supervisor – Dr. Kyeong kang, at Kyeong.Kang@uts.edu.au; +61 2 95141912) or Co-supervisor – Dr. Daniel Chandan, at (Daniel.Chandran@uts.edu.au; +612 95141827).or my local supervisor for data collection in Saudi Arabia Othman M. Asiry at (Asiry@Uj.edu.sa) ; Ph: +966 [redacted] You will be given a copy of this form to keep.

NOTE:

This study has been approved in line with the University of Technology Sydney Human Research Ethics Committee [UTS HREC] guidelines. If you have any concerns or complaints about any aspect of the conduct of this research, please contact the Ethics Secretariat on ph.: +61 2 9514 2478 or email: Research.Ethics@uts.edu.au], and quote the UTS HREC reference number: ETH19-4262. Any matter raised will be treated confidentially, investigated and you will be informed of the outcome.

CONSENT FORM

ETH19-4262: Human and Cultural Factors for Supporting Big Data Analytics in Higher Education Sectors: A Study of Saudi Arabia Universities.

I ________________________________agree to participate in the research project **Human and Cultural Factors for Supporting Big Data Analytics in Higher Education Sectors: A Study of Saudi Arabia Universities** being conducted by *Maher Mohammed Asseri,* 15 Broadway, Ultimo New South Wales 2007, Phone no +6102 9514 2000. I have read the Participant Information Sheet, or someone has read it to me in a language that I understand.

I understand the purposes, procedures and risks of the research as described in the Participant Information Sheet.

I have had an opportunity to ask questions and I am satisfied with the answers I have received.

I freely agree to participate in this research project as described and understand that I am free to withdraw at any time without affecting my relationship with the researchers or the University of Technology Sydney.

I understand that I will be given a signed copy of this document to keep.

I agree to be:

☐ Audio Recorded

☐ Video recorded via zoom & Observed by Researcher during the interview

I agree that the research data gathered from this project may be published in a form that:

☐ Identifies me

☐ Does not identify me in any way

☐ May be used for future research purposes

I am aware that I can contact *Maher Mohammed Aseeri at (Maher.m.aseeri@student.uts.edu.au); Ph: +61)* if I have any concerns about the research.

____ Date ____/____/____ Name and Signature [participant]

____ Date ____/____/____

Name and Signature [researcher or delegate]

Appendix H: Information Sheet& Consent Form for Interviews Arabic Version

العوامل البشرية والثقافة التنظيمية لدعم تحليلات البيانات الضخمة في التعليم العالي السعودي
4262-ETH19

من يقوم بالبحث؟

اسمي ماهر محمد عسيري وأنا طالب في جامعة سيدني للتكنولوجيا (UTS .)مشرفي الرئيسي هو د .كيونغ كانغ والمشرف المشارك هو دانيال تشاندران(

ما هو موضوع البحث؟

يهدف هذا البحث إلى معرفة تأثير العوامل البشرية والثقافية إلى جانب التكنولوجيا التي تدعم تحليل البيانات الضخمة لاتخاذ قرارات فعالة من قبل الإدارة العليا وتحسين أداء المنظمة في الجامعات السعودية المختارة.

ما سبب توجيه هذه الدعوة لي؟

تمت دعوتك للمشاركة في هذه الدراسة لأنك عميد كلية تكنولوجيا المعلومات والتعلم عن بعد، وتعمل في إحدى الجامعات السعودية المختارة ولديك معرفة ذات علاقة بموضوع البحث.

إذا وافقت على المشاركة، فما الذي سيتضمنه ذلك؟

إذا قررت المشاركة، فسأقوم بدعوتك إلى مقابلة شبه منظمة مدتها 55 دقيقة- ساعة واحدة، وسيتم تسجيلها صوتيا ونسخها كما سيتم كتابة الملاحظات أثناء المقابلة من قبل الباحث.

هل هناك أي خطر أو إزعاج قد ينجم عن المشاركة في هذه المقابلة ؟

لا يوجد لهذا البحث أي خطر خلال المقابلة لأن هذه الدراسة صممت بعناية من قبل الباحث؛ ومع ذلك، فمن المحتمل أنك قد تواجه بعض الأمور غير المريحة لأن مدة المقابلة هي 55 دقيقة - 1 ساعة وسيتم تسجيل المقابلة بواسطة جهازين لتسجيل الصوت.

هل يجب على المشاركة في البحث؟

المشاركة في هذه الدراسة طوعية والأمر متروك لك تمامًا سواء قررت المشاركة أم لا.

ماذا سيحدث في حال رفضت المشاركة؟

إذا قررت عدم المشاركة ،فإنه يحق لك رفض أو سحب مشاركتك في أي مرحلة من هذه المقابلة، وهذا لن يؤثر على وظيفتك أو انتسابك التنظيمي، وإذا كنت ترغب في الانسحاب من الدراسة بمجرد بدء الدراسة ،فأيضاً يمكنك القيام بذلك في أي وقت دون الحاجة إلى تقديم سبب، من خلال الاتصال على ماهر محمد عسيري عبر:
Maher.m.aseeri@student.uts.edu.au (؛ *Ph: +61* [redacted]) ؛ +966 [redacted]

ومع ذلك، إذا قمت بالانسحاب من الدراسة، فقد لا يكون من الممكن سحب بياناتك من نتائج الدراسة إذا كانت هذه البيانات قد تمت إزالتها بالفعل.

وفي حال قررت ترك المشروع البحثي، فلن نجمع معلومات شخصية إضافية منك، رغم أنه سيتم الاحتفاظ بالمعلومات الشخصية التي تم جمعها بالفعل لضمان إمكانية قياس نتائج المشروع البحثي بشكل صحيح والامتثال للقانون، كما يجب

عليك أن تدرك أن البيانات التي يتم جمعها حتى وقت السحب ستشكل جزءًا من نتائج مشروع البحث، أما إذا كنت لا ترغب بأن يفعلوا ذلك، فيجب أن تخبرهم قبل الانضمام إلى مشروع البحث.

السرية

من خلال التوقيع على نموذج الموافقة، فإنك توافق على قيام فريق البحث بجمع واستخدام المعلومات الشخصية عنك لمشروع البحث، وسيتم التعامل مع كل هذه المعلومات بسرية تامة، كما سيتم تخزين سجلات البيانات بالطرق التالية:
التسجيل الصوتي والنصوص حيث سيتم حفظ البيانات على *UTS OneDrive*، وسيتم حفظ نسخة احتياطية محمية بكلمة مرور عن طريق نظام التخزين السحابي الجامعي إلى جانب نظام إدارة بيانات *UTS Stash*"؛ ولن يتم استخدام معلوماتك إلا لغرض هذا المشروع البحثي، ونود تخزين معلوماتك لاستخدامها في المستقبل في المشروعات البحثية التي تعد امتدادًا لهذا المشروع البحثي؛ مع التأكيد على أنه في جميع الحالات، سيتم التعامل مع معلوماتك بسرية تامة.

ماذا إن كان لدي مخاوف أو شكوى؟

إذا كانت لديك مخاوف بشأن البحث وتعتقد أنه يمكنني أو يمكن للمشرفين مساعدتك، فلا تتردد في الاتصال بي ماهر محمد عسيري على *(Maher.m.aseeri@student.uts.edu.au* ؛ *Ph: +61*[redacted]*)* ؛ [redacted] +966 أو المشرف الرئيسي د .كيونغ كانغ عبر (Kyeong.Kang@uts.edu.au ؛ 95141912 2 61+(أو المشرف المشارك - الدكتور دانيال تشاندان عبر (Daniel.Chandran@uts.edu.au ؛ 95141827 2 61+) أو المشرف المحلي الخاص بي لجمع البيانات في المملكة العربية السعودية د.عثمان محمد عسيري عبر (Asiry@Uj.edu.sa؛ Ph: [redacted] 966+(سوف تحصل على نسخة من هذا النموذج للاحتفاظ بها.

ملحوظة:

تمت الموافقة على هذه الدراسة بما يتماشى مع المبادئ التوجيهية للجنة أخلاقيات البحوث الإنسانية لجامعة سيدني] UTS HREC[؛ في حال كانت لديك أي مخاوف أو شكاوى بشأن أي جانب من جوانب إجراء هذا البحث، فيرجى الاتصال بأمانة الأخلاقيات على الرقم: 2478 9514 2 61+ أو عبر البريد الإلكتروني: Research.Ethics@uts.edu.au[، واقتبس الرقم المرجعي للجنة: ETH19-4262 وسيتم التعامل مع أي مسألة تثار بشكل سري، وسيتم التحقيق معك ثم إبلاغك بالنتيجة.

إنني هنا ،أوافق على المشاركة في المشروع البحثي "العوامل البشرية والثقافية لدعم تحليل البيانات الضخمة في قطاعات برودواي، أوليمو 15التعليم العالي: دراسة في جامعات المملكة العربية السعودية والتي يجريها ماهر محمد عسيري، +؛ ولقد قرأت ورقة معلومات المشارك. 6102 9514 2000، رقم الهاتف2007نيو ساوث ويلز

إنني أدرك أهداف وإجراءات ومخاطر البحث كما هو موضح في ورقة معلومات المشارك. ولقد أتيحت لي الفرصة لطرح الأسئلة وأنا را ض عن الإجابات التي تلقيتها.

إنني أوافق بحرية على المشاركة في هذا المشروع البحثي كما هو موضح وأدرك أنني حر في الانسحاب في أي وقت دون التأثير على علاقتي مع الباحثين أو جامعة سيدني للتكنولوجيا.أدرك أنه سيتم إعطائي نسخة موقعة من هذا المستند لأحتفظ بها.

إنني أوافق على:

تسجيل المقابلة صوتي اً

كتابة الملاحظات أثناء المقابلة من قبل الباحث

أوافق على أنه يجوز نشر بيانات البحث التي تم جمعها من هذا المشروع في شكل:

يحدد هويتي

لا يحُدد هويتي بأي شكل من الأشكال

يمكن استخدامها لأغراض البحث في المستقبل

أدرك أنه يمكنني الاتصال بـ ماهر محمد عسيري على)*Maher.m.aseeri@student.uts.edu.au*(؛ *Ph*:
61+(في حال كان لدي أي مخاوف بشأن البحث.

اسم وتوقيع المشارك ____________________ التاريخ ——/——/——

اسم وتوقيع الباحث ____________________ التاريخ ——/——/——

Appendix I: Constructs, Definitions, Hypothesis, and Research Questions

Construct	Brief Description	Supported studies	Research Question	Hypothesis
BDP on BDS	BDAPs is the first social aspect in the current study which include IT academic & non-academic staff, and data scientists. The role of BDPs on BDSQ is securing big data which stored in BDSQ. The same for the privacy of big data, BDAPs ensure that the privacy of stored big data complies with the standard of data privacy. Finally, BDAPs are responsible for the quality of big data which could lead to improved decision-making by top management.	(Bostrom and Heinen (1977)(Davenport et al. (2012)(Niederman et al. 2016). Wamba et al. (2017) Charif (2017) Dremel et al. (2018) Cronemberger 2018) Russom (2011)	To what extent do Big Data Analytic performers BDAPs, namely IT staff, influence big the security, privacy, and quality of big data in Saudi Arabian universities?	Big data analytic performers, including IT academic staff, IT non-academic staff, have a positive effect on big data security privacy and quality
BDP on BDT	BDAPs also play crucial roles in performing BDTs which include storing big data, analyse, and visualise them.	T.H. Davenport, (2014, & 2017). Kim et al. (2016) Herschel and Miori (2017) (Mckibbin and Member 2019)	To what extent do Big Data Analytic performers BDAPs, namely IT staff and data scientists influence big data tasks?	Big data analytic performers, positively affect BDTs including storing analysing, and visualising big data.
OC on BDS	Organisational culture is the second social aspect in our study that includes accepting and adapting to BDA technological improvements. In particular, the impact of OC on BDSQ that include in big data security, privacy, and quality.	(Cronemberger 2018)(Sam and Chatwin 2019). (Iivari and Huisman 2017) Sam and Chatwi (2019) Dubey et al., (2019) Iivari and Huisman (2017) Dasgupta and Gupta (2019)	To what extent do social factors, namely organisational culture, impacts BDSQ i.e., security, privacy, and quality?	Organisational culture of accepting and adapting technological improvements has a positive effect on big data system quality including big data security, privacy, and quality.
OC on BDP	In this construct, organisational culture that includes accepting and adapting to new BDA technological improvement could impact BDAPs in accepting BDA technological improvements.	(Madhlangobe (2016) Costanza et al. (2016) Jarrah et al.,(2020) Gupta (2019) Costanza et al. (2016)	To what extent do social factors, namely organisational culture, impact IT staff, and data scientists?	Organisational culture of accepting and adapting technological improvements has a positive effect on big data analytic performers, such as data scientists

OC on BDT	Organisational culture could have an impact on BDTS. OC could encourage the whole organisation to store big data, analyse, and visualise them for improving the decision-making by top management.	Gupta and George (2016), Mikalef, Pappas, Krogstie, & Giannakos (2017) Sjusdal & Lunde's (2019.	To what extent does social factors, namely organisational culture, impact BDATs?	Organisational culture of accepting and adapting technological improvements has a positive effect on BDTs including storing, analysing and visualising big data.

OC on DES	In this construct, we proposed that OC has an impact on improving decision-making, where the acceptance of BDA technological improvements leads to improve decision-making by top management since the top management uses analysed data for among their decisions.	Dasgupta and Gupta (2019) Ax & Greve (2017(Attar 2020) Lunde et al.,(2019)	To what extent do social factors, namely organisational culture, influence the decision-making by top management?	Organisational culture of accepting and adapting technological improvements has a positive effect on improving the decision-making by top management.
OC on OP	Organisational culture is also seen as the main factor that could improve overall university performance, where BDA is taking place to enhance decision-making, leading to improve university performance.	Elgendy and Elragal (2016) Aldholay et al. (2018) Adrian et al.,(2018)	To what extent do social factors, namely organisational culture, affect a university's performance?	Organisational culture of accepting and adapting technological improvements positively improves university performance by creating business values and academic outcomes.

BDS on DES	BDSQ consider the technical part that includes big data security, privacy, and quality. All of these, taken together, could lead to improve decision-making since the top management staff make a decision based on the secure, private, and good quality of analysed data.	(Madhlangobe 2016)(Amiri 2017) (DeLone & McLean 2003)(Fosso Wamba et al. 2018)(Cronemberger 2018).	To what extent do BDSQ, namely big data security, privacy, and quality, enhance top management's decision-making in Saudi Arabian universities?	The quality of big data systems, including big data security, privacy, and quality, positively impacts top management's decisions.
BDT on DES	BDT is the second part of the technical aspects in this study. BDT includes storing big data from various sources, analysing these data, and visualising them for top management staff to make their decisions based on them.	(Lenard 2014,) Foss_Dissertation_ImplementingAnalytics, (Dubey et al. 2019). (Bostrom and Heinen 1977) (Saggi & Jain 2018; Korherr & Kanbach 2021)	To what extent do technical factors, namely big data tasks, i.e., storing, analysing, and visualising big data, enhance top management decision-making in Saudi Arabian universities?	Big data tasks, including storing, analysing, and visualising big data, have a positive impact on improving the decision-making by top management.
DES on OP	In this construct, improving the decision-making by top management could lead to enhance overall university performance. These improvements include creating business values and improving academic outcomes.	(Bostrom and Heinen 1977) (Saggi & Jain 2018; Korherr & Kanbach 2021) (Frisk and Bannister 2017)Janssen et al. (2017)Adrian et al. (2018)	Does improving Decision making by top management will improve university performance?	Improving decision-making by top management has a positive impact on university performance.