Decision-making in data-intensive environments and its impact on organisational design: Dynamic capabilities approach

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ABBREVIATIONS

BD	Big Data
BDA	Big Data Analytics
BI	Business Intelligence
CFO	Chief Finance Officers
CIO	Chief Information Officers
DC	Dynamic Capabilities
GTM	Grounded Theory Method
HR	Human Resources
ICT	Information and Communication Technologies
IS	Information Systems
IT	Information Technology
KBV	Knowledge-Based view
KM	Knowledge Management
RBV	Resource-Based View
RDBMS	Relational Database Management Systems

STATEMENT OF ORIGINAL AUTHORSHIP

This thesis does not contain any material that has been accepted for the award of other degrees or diplomas at any other university or equivalent institution, and I hereby state that it does not contain any material that has been written or published by another individual, except where due reference is made in the text of the thesis.

Hadi Karami 08/11/2022

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Abstract

The main purpose of this research is to investigate how organisations that are dealing with large datasets can improve their decision-making processes by developing new and reconfiguring existing capabilities. Business environments are getting increasingly dynamic and data-intensive because of emerging technologies and advances in data science, information and communication technologies, which require enterprises to make regular and faster decisions. In this regard, one of the new phenomena that has revolutionised businesses is big data providing organisations with opportunities and also challenges. Based on big data's capability to provide useful information for dynamic decision-making processes, this study aims to investigate how big data influences decision-making processes and, consequently organisational design. It seeks to identify how organisations change and design either of those processes and their organisational structure to make sense of big data. This study uses an integrated approach of dynamic capabilities as a lens to identify the sources of dynamism in organisations. This approach takes into account three levels of dynamism including individual, interpersonal and corporate levels, which are employed in the process of data analysis. In terms of methodology and methods, this study uses a multiple case-study approach in order to gain rich and illuminating data about each case and the phenomenon under investigation. The cases of this study are chosen from organisations that are using large datasets as a source of information for decision-making based in the UK. Nine cases were studied, from which twelve people were interviewed. Interviewees included business intelligence and analytics experts and managers who have a deep understanding of organisational and information-processing mechanisms. The reasoning technique is abductive, meaning that some of the concepts are taken from the literature and constant comparison are made between literature and data to identify emerging concepts. This study, contributes to decision-making theory by providing insights about dynamic decision-making in the context of big data and a better understanding of organisational strategies for working with and leveraging value from big data. In addition, for the practical aspect, it contributes to guiding practitioners in evaluating their organisations to inform improvement to become better enabled for big data-driven decision-making.

1. Chapter one: Introduction

1.1. Introduction

This chapter highlights the background of the study, the importance of the research, and the supporting and underlying theoretical assumptions that shape the research approach of the study. The intention is to make the reader understand the motivation behind the research and how it relates to the problem it tackles. This is followed by the rationale of the research and the objectives required to be addressed.

Fast developments in Information and Communication Technologies (ICT), social networking, e-commerce websites, and various types of digital technologies have resulted in the emergence and rapid growth of Big Data (BD), making business environments increasingly dynamic. At its core, this study aims to understand how organisations can cope with those environments by changing decision-making processes and redesigning their companies, particularly in terms of developing dynamic capabilities.

Three fundamental areas of this study include decision-making, organisational design and structure, and Dynamic Capabilities (DC). Furthermore, in light of the research question that is concerned with investigating how big data influences organisational decision-making processes and, consequently, organisational design in terms of developing new capabilities, this chapter provides an overview of the research question and methods used in this study and emphasises their significance. In doing so, the background of the study has been provided, which highlights the research question and its importance. This is then followed by the theoretical and practical contributions of this study.

1.2. Research problem

Due to the emergence and evolution of new technologies, such as information systems, the global business environment is becoming more complex. In 2018, the governments and firms of the world spent almost $5 trillion on various IT equipment and services. Most of this went toward consulting and management services, which are designed to help firms take advantage of these new opportunities. Most of the value of an IT investment is derived from the changes that occur within a firm's culture and organisational structure (Laudon and Laudon, 2022).

In addition to the technological changes that are happening, the other factors that are contributing to the growth of the global information technology market are also expected to affect the market's future. In 2023, the market is expected to reach $6.2 trillion. While Europe and America are expected to account for most (70%) of the global investment in IT, other regions such as Asia Pacific, Latin America, and Eastern Europe are expected to contribute to the market's growth (Laudon and Laudon, 2022).

Business environments are getting increasingly complex and fast-changing due to different factors, specifically advances in data science, information and communication technologies (Grable and Lyons, 2018). These changes might bring about opportunities (e.g. improving business performance and growth, shifting innovation borders, forecasting in the future, etc.) and also pressures (dealing with a huge amount of unstructured data which is beyond the capability of traditional databases) for organisations, forcing them to respond quickly and in an innovative way to make the most of opportunities and avoid problems (Müller et al., 2018). "Such advances in digital technologies offer ripe opportunities for firms with superior dynamic capabilities to gain an advantage by deploying them faster and smarter than their rivals" (Day and Schoemaker, 2016:70).

Such activities require enterprises to make regular and quick strategic and operational decisions. Accordingly, such choices might require significant amounts of real-time and relevant data, information and knowledge. Over the past few years, the amount of data businesses use, has massively increased in volume, variety and velocity. Big data is one of the influential factors in making business environments increasingly dynamic, defined as extensive data sets entailing various features such as volume, velocity, variety, value and veracity (5Vs) (Samuel Fosso Wamba et al., 2017; Grable and Lyons, 2018). There are various data sources such as social media, the Internet of Things, smartphone applications, healthcare, financial transactions, industry and personal computers (Chen et al., 2014). Due to the increasing number of these types of data sources, the decision-making process has become more dynamic and complicated. Those decision-making processes can affect how the organisation collects, stores, and analyses data (Chen et al., 2014).

In the last decade, big data has been gaining widespread attention from management scholars as it can help organisations drive their operations and improve their customer support. Many organisations are currently investing in developing Big Data Analytics (BDA) capabilities to derive actionable insight from their data. The objective of these capabilities is to enable individuals and organisations to make informed decisions. Due to the increasing amount of processing power that an analyst can acquire with the help of big data analytics, the need for organisations to use the data across various day-to-day management areas has become more prevalent. This has also led to the emergence of new management domains that are related to BDA. However, there is still a lack of research on these new management areas leveraging BDA techniques' full potential (Kushwaha et al., 2021).

Big data is gaining considerable attention in academic and corporate investigations due to its potential to generate value for businesses, shift innovation frontiers, transform decision-making processes, and enhance productivity and competitiveness (Wamba et al., 2015). Big data analytics would contribute to organisational performance by decreasing customer acquisition costs, improving the review, sensing business environments more effectively, and transforming knowledge created by analytics into decision-making processes (Ferraris et al., 2018; Müller et al., 2018; Davenport et al., 2012). Therefore Business Intelligence (BI) and analytics have become among the top priorities for CIOs and CFOs (Chief Information and Finance Officers) (Müller et al., 2018).

Studying the impacts of big data on organisations requires focusing on several key areas such as knowledge management, capabilities necessary to deal with big data, organisational routines and processes, and data itself as a source (Rialti et al., 2019). Moreover, analysing those data sets requires new tools, techniques and capabilities because they are too voluminous or unstructured to deal with traditional methods (Davenport et al., 2012). In doing so, how decision-making processes are changing and the possible drivers of those changes need to be investigated. Moreover, in spite of vast amounts of research in the decision-making area, Sharma et al. (2014) argue that the impact of business analytics on organisations and their performance need to be studied meticulously regarding the roles of organisational, strategic and behavioural issues. Particularly, much attention needs to be paid to the decision-making and resource allocation processes that may need to be changed to create value from the use of business analytics. They also mention that despite the previous studies, more recent research highlights the need for changes in organisational design to capture the value of business analytics effectively.

This study investigates how organisations make sense of big data by restructuring their decision-making processes and developing new capabilities. In the current technological climate, data processing is becoming a major concern for many organisations in many sectors. Such organisations constantly face the challenge of making rapid decisions requiring agile data processing, flexible decision processes, and dynamic capabilities.

1.3. Research question and objectives

This study aims to investigate how big data influences organisational decision-making processes and, consequently, organisational design in terms of developing new capabilities. In other words, organisations make sense of the sheer amount of data available to them by changing their decision-making processes and developing new capabilities to cope with increasingly complex and dynamic environments.

Specifically, the research question will be how big data influence decision-making and, consequently organisational design. The objectives of this research include:

- To identify the ways in which decision-makers in data-intensive environments are changing their decision-making processes.
- To identify the factors which decision-makers consider most influential in driving those changes.
- To identify how those changes influence organisational design to enhance dynamic decision-making.

- To develop a framework to enable decision-makers to assess and improve their strategies for adapting to data-intensive environments, including the required capabilities.

1.4. Research design and methodology

For this study, a mono-qualitative method is chosen based on the interpretivism philosophical stance of the researcher and also the nature of the research question that aims to investigate a phenomenon within its natural context. This study seeks to study the decision-making processes (as a particular management activity), and how managers design their organisations by developing dynamic capabilities to keep pace with fast-changing and data-intensive environments. In doing so, a multiple case study approach is chosen for this research to gain an in-depth understanding of the topic concerned. The cases of this study include organisations that are using large datasets as a primary source of information for decision-making based in the UK. For this study, nine organisations are selected, from which twelve people are interviewed. In this regard, business intelligence and analytics experts, data analysts, data scientists, data officers and managers (from various levels of organisations) who deeply understand organisational and information processing mechanisms are interviewed.

The grounded theory method is used to analyse the data. In this regard, an abductive (constant shift between data and literature) reasoning technique is used to analyse the data where new theories and concepts have emerged as a result of coding. Emerged codes shaped open codes that resulted in subcategories and eventually did fit into major themes coming from the literature review. The emerging concepts and theories and their relationship are then discussed, shaping the study's conceptual model.

1.5. Structure of thesis

This thesis is structured into six chapters in order to support the argument of this study. The first chapter is concerned with introducing the topic being studied and highlights its importance within Information Systems (IS) studies. It also outlines the research question and the overall structure of the thesis. The second chapter reviews the current literature on the main concepts of this study in light of the research question. Accentuating and discussing those core concepts provide a theoretical foundation for this study and gradually develops into a conceptual model that eventually guides and informs the rest of the study. Chapter three of this study is concerned with methodology, arguing the philosophical stance of the researcher, reasoning techniques, grounded theory method, data collection, and analysis techniques adopted to address the research question.

Chapter four is concerned with analysing the core themes that emerged from the data. The mentioned chapter provides the findings about three major themes of this study, including decision-making, dynamic capabilities and organisational design and structure. This is followed by chapter five, where the study's findings are discussed in relation to the existing literature, and their significance are presented. In doing so, new emerging concepts and the relationship between them and the literature are also delineated.

The final chapter presents the study's summary and presents conclusions concerning the research questions. Theoretical contributions and implications for practice are also discussed in this chapter. Furthermore, the challenges and limitations of the study and also ideas for future research are provided in this chapter.

2. Chapter two: Literature review

2.1. Introduction

The prime goal of this chapter is to provide a conceptual framework for the study of big data, decision making and dynamic capabilities. It aims to explore the various aspects of an organisation's structure and operations, such as its organisational capabilities that help improve decision-making in data-intensive environments. The chapter also reviews the existing relevant literature that supports the conceptual foundation of this study.

The review process for this chapter involved conducting a literature search through various resources. These included books, journals, and electronic journals. The goal of the literature review is to provide a comprehensive analysis of the literature that supports the study's main research question. It also helps the researcher identify the various theoretical approaches that have been used in the field. This process allows the researcher to make an informed decision when it comes to conducting the study. The review process also helps the researcher improve the quality of the study by allowing them to observe how other researchers have conducted their studies. It additionally helps the researcher identify the most effective method to carry out the study. Doing a literature review also helps the researcher gain a deeper understanding of the field of research that he or she is working on. It also allows researchers to identify the various issues related to the study (Jupp and Sage, 2006).

In order to support the conceptual foundation of the study, this chapter reviews the following concepts: business analytics (information technology and big data analytics), big data (definitions and characteristics of the phenomenon as well as the opportunities, challenges and implications of it for the organisational information processing mechanisms and design), organisational design and structure and their important role in regulating information flow within the organisations, decision-making (focusing on the various styles and decision making), dynamic capabilities (focusing on the main dynamic capabilities and how they could be developed to make sense of big data and facilitate the value creation from it, and enhance the dynamic decision making).

2.2. Business analytics

This section is dedicated to reviewing the concept of business analytics, its significance for organisations and its link with other IT infrastructures and resources. Before entering the discussion, it is worth mentioning the difference between Business Intelligence (BI), IT and business analytics. When applied to data, *analytics* can create insight. It can encompass various disciplines, such as statistics, data management, and business intelligence (Liebowitz, 2014). For instance, machine learning and advanced analytics are techniques that seek to analyse and predict the future. Instead of just summarising what has happened, they try to understand the factors that have happened and predict what will happen next. When it comes to creating value, insight has to be acted on. In *business analytics*, the goal is to take the insight and use it to improve the company's performance (Liebowitz, 2014).

The term IT is widely used in the Information Systems (IS) field. An information technology infrastructure is a type of shared technology resource that enables a firm to provide its customers with the necessary information systems. This includes hardware, software, and services that are shared across the organisation (Laudon and Laudon, 2020). It also enables the firm to manage its internal processes and serve its customers. Around 25% to 50% of the IT expenditures of large corporations are allocated for infrastructure. Financial services firms are known to have the most significant share of this investment (Laudon and Laudon, 2020).

In the same vein, IT could be defined as “[t]he use of computers and telecommunications equipment (with their associated microelectronics) to send, receive, store and manipulate data. The data may be textual, numerical, audio or video, or any combination of these” (Daintith et al., 2005:440). Business intelligence includes both IT and BA (Business Analytics). IT is concerned with the technical aspects of BI involving data gathering, storing and reporting, whereas BA’s focus is largely on supporting analytics-based decisions to deal with problems (Bartlett, 2013). Accordingly, Mandal (2018) refers to a subtle difference between IT and big data analytics capabilities. In this regard, IT capabilities are considered as a backbone of big data analytics attempting to deploy the basic IT infrastructure, whereas BDA is trying to deal with specific features of big data by relying on IT capabilities (Zhu et al., 2021). Hence, the effectiveness of BDA is contingent upon IT capabilities. Big data and analytics are becoming more prevalent in organisations as they seek to capture the potential of their data and create value. This process (BDA) involves analysing and implementing various statistical and quantitative methods to improve the efficiency of organisations' operations (Zhu et al., 2021).

As mentioned earlier, BDA's effectiveness depends upon various factors such as IT infrastructures. Therefore it is important to understand the significance of the tools and capabilities required for the effectiveness of big data analytics. According to a bibliometric literature review conducted by Rialti et al. (2019) on big data and dynamic capabilities, new data analysis tools based on artificial intelligence are required to handle such massive data sets. Accordingly, "Collaborations, knowledge exchange and big data analytics, which can be facilitated by the effective use of technology, heavily determine big data decision-making capabilities" (Shamim et al., 2018:4). Meanwhile, some other ad-hoc processes might be defined by organisations in various stages of acquisition, modelling, analysis, integration, and interpretation that need to be considered in BDA capabilities (Shamim et al., 2018).

The importance of IT infrastructures was mentioned earlier in supporting business analytics capabilities. However, clarifying whether it could be a source of competitive advantage for organisations might be useful. From the resource base view (Barney, 2001), IT itself is not considered a source of competitive advantage based on the fact it is not a unique resource and is available to other competitors (Devece et al., 2017). However, its integration in conjunction with other intangible assets might contribute to capabilities resulting in lasting competitive advantage (Devece et al., 2017). In other words, IT infrastructures would facilitate the ability of organisations to detect, process and communicate information on dynamic markets (improving organisational agility) (Battleson et al., 2016). Mikalef and Krogstie (2018) believe the importance of IT governance has been studied broadly. According to the mentioned discussions, It seems that the role of IT in facilitating information flow has been studied widely. However, according to the academic debate mentioned earlier, IT capabilities are not enough to address current data-intensive environments in terms of handling massive datasets to provide insight and improve organisational information processing mechanisms. There are other factors involved in generating value from information within organsiations that could be used in conjunction with IT capabilities. In this regard, there is little effort in studying and establishing big data governance, defined as a firm's ability to organise its resources to maximise the value and insight that could be generated from information (Mikalef and Krogstie, 2018).

As discussed earlier, business analytics is a process that helps companies extract valuable insight from their data. However, without action, this insight rarely leads to an economic return. Instead, it's about making the necessary changes to improve the organisation's efficiency. In addition to being able to create insight, business analytics also focuses on supporting the implementation of change management. This discipline is very important because it can help people identify the value of a change and get the necessary support to make it happen (Liebowitz, 2014). In general, IT infrastructures and big data analytics capabilities are not independent. As mentioned earlier, the capabilities of the organisation's IT infrastructure are often referred to as the backbone of big data analytics. In addition, BDA is usually focused on dealing with the specific features of big data (Bartlett, 2013). As the number of organisations implementing big data and analytics continues to increase, the need for effective and efficient solutions is also growing. Therefore, the effectiveness of big data analytics relies on IT infrastructures, as well as change management. The following section reviews the concept of big data, its characteristics, opportunities and challenges created by it, and its significant implications for organisations that are using big data as a key source of information.

2.3. Big data

This section aims to present the literature review of big data, contributing factors to the emergence of big data, its characteristics, various sources of big data, opportunities and challenges brought about by big data, its implications for organisations and decision-making mechanisms within the organisations, and main current technologies available to handle big data. Reviewing the mentioned concepts would provide the researchers with a better understanding of the impacts of big data on organisations and their various elements.

Fast developments in information and communication technologies, social networking, e-commerce websites, and various types of digital technologies have resulted in the emergence and rapid growth of big data (Maroufkhani et al., 2020). For example, figure 2-1 shows the exponential growth in computational power and the decline in the size of microchips which is one of the main drivers of IT development (Laudon and Laudon, 2020). The rise of the data-driven economy has created a paradigm shift in how organisations approach their business. And this new approach is expected to lead to the emergence of new strategies and methods to transform their competitive forces (Ranjan and Foropon, 2021).

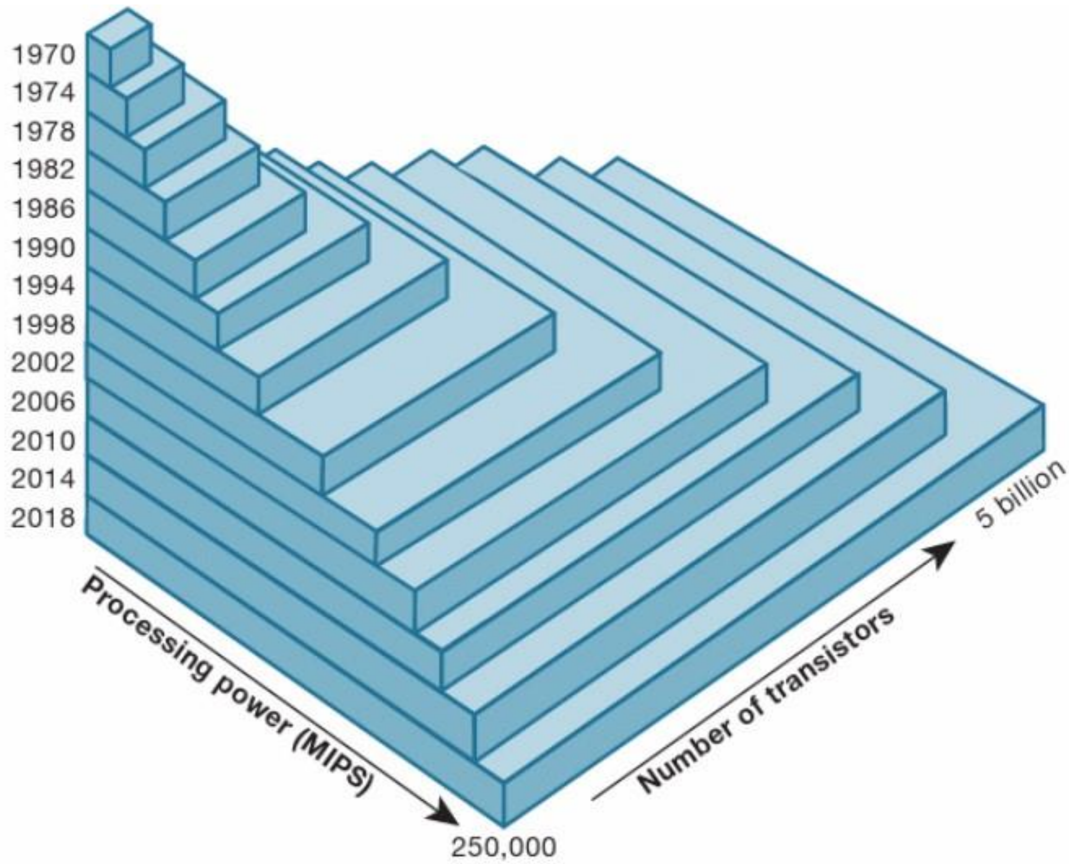

Figure 2-1 Microprocessor performance over the years 1970-2018 (Laudon and Laudon, 2020:204)

According to Laudon and Laudon (2022), before the rise of social media and web traffic, most data collected by organisations were typically stored in relational databases. Now, it is becoming more complex to collect and analyse data from different sources, such as social media content and web traffic. Due to the complexity (this is because most of the data collected are unstructured, which poses significant challenges in terms of analysing the data and getting insight from it) of the data collected by organisations, it is not suitable for use in traditional relational databases anymore. Instead, they are being referred to as big data sets, which are collections of data that are so large that they are beyond the capabilities of traditional databases (Laudon and Laudon, 2020).

As mentioned, big data is a new phenomenon in the field of data science that has attracted the attention of scholars and scientists. It was first coined by Francis Diebold back in 2003. He said that the term came about due to the quality and quantity of data that emerged due to various developments and technologies (Diebold, 2012; Moorthy et al., 2015). Big data is “the term applied to data sets that are not able to be acquired, accessed, analysed using analytics and or an application in a reasonable amount of time” (James, 2013:128). According to another definition, big data (huge datasets) possesses various features such as volume, variety and velocity (Mcafee and Brynjolfsson, 2012). Two main models of definitions have been mentioned (Chen et al., 2014): 3Vs and the 4Vs models. The former model refers to:

Volume (exponentially growing in terms of volume of data): for example, a single jet engine can generate up to 10 terabytes of data within 30 minutes. There are over 25,000 flights on an average day, and Twitter generates more than eight terabytes of data a day (Laudon and Laudon, 2020). To give another example, the rise of Internet users has created a vast amount of data that can be collected and analysed by various devices and systems. According to IDC, by 2025, 75% of the world's population will be using online data (Kumar, 2021).

Velocity (referring to the rate at which data is being created and timeliness in the acquisition and utilising): For instance, tsunamis and earthquakes can be detected early with the help of high-velocity analytical tools and sensors that require real-time data analysis capabilities (Blewitt et al., 2009). Another example could be a need to quickly analyse the financial transactions of credit cards for fraud detection.

Variety: it refers to the heterogeneity and complexity of various types of data available such as text, image, signal, audio, video etc (Chen et al., 2014). Depending on the needs of companies, they might need different tools to deal with this particular characteristic of big data. For example, video analysis tools and techniques differ from those used to analyse sensory data.

The latter model adds value to the equation, while the former does not. A fourth "V" refers to the knowledge and extraction of value from big data. White (2011), in his definition of BD, goes beyond the capability to handle massive data sets and refers to new sets of technological tools and possibilities which are capable of handling data of all types. Gantz and Reinsel (2012) define BD in terms of data, analysis, and data presentation.

Figure 2-2 shows the exponential decline in the prices of data storage between 1950-2018 which has contributed significantly to the volume of data being produced. At the same time, the rapid decline in the cost of communication over the telephone and over the internet has created an explosive growth opportunity for computing and communication, which also refers to the second characteristic of big data (velocity).

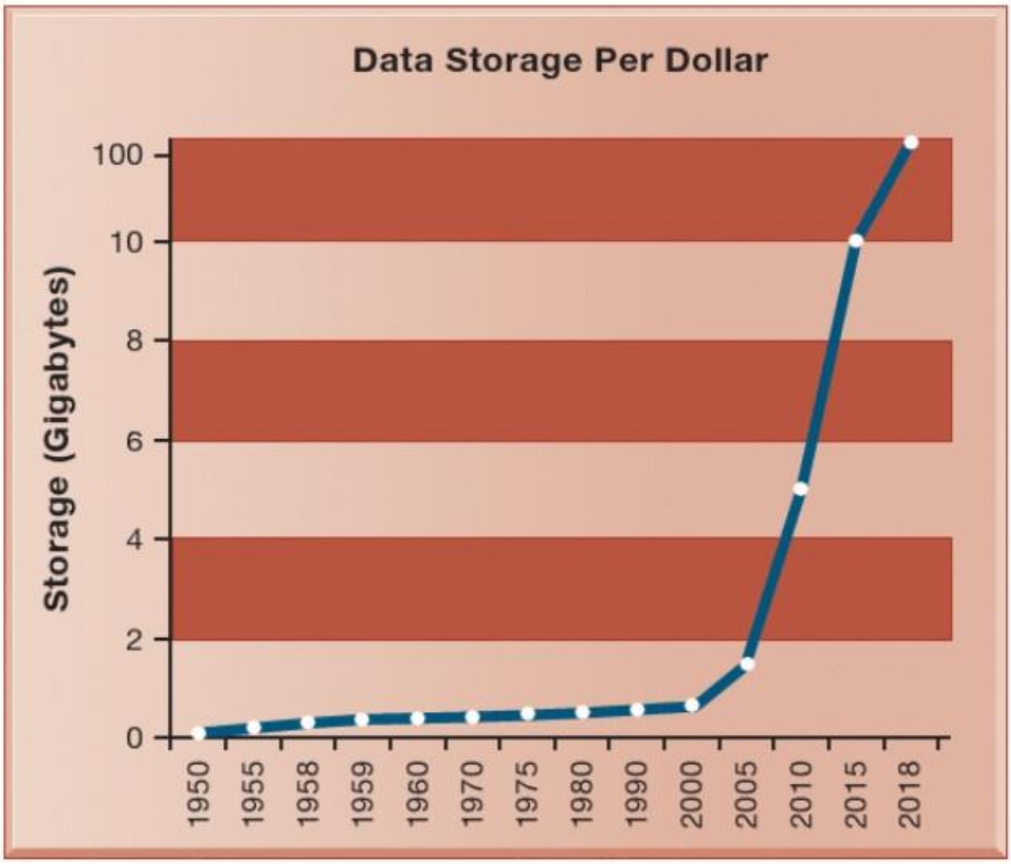

Figure 2-2: The amount of data storage cost per dollar (Laudon and Laudon, 2020:206)

Big data brings about opportunities and challenges for organisations that are dealing with it. Handling such massive data sets is not a straightforward process and requires interplay between various organisational capabilities and elements. In this sense, Boyd and Crawford (2012) highlight the interplay between three key aspects, including technology (computational power), analysis (identification of patterns in data), and mythology (a cultural aspect of BD referring to believing in the potential of BD in providing insights and intelligence).

According to the definitions mentioned above, it seems that organisations need new ways of handling such massive data sets that possess various characteristics. For example, technology-based resources are required to collect, analyse, and interpret the enormous data sets, and those technologies and capabilities could benefit various areas of the businesses such as security, operations, marketing intelligence, decision-making, supply chain management and more (De Camargo Fiorini et al., 2018). In the following sections of the literature review, some of the capabilities that organisations can utilise to take advantage of such data sets are discussed and reviewed.

Another key area to focus on is the sources of data. The rise of digital networks has revolutionised the way organisations collect and use data (Zhu et al., 2021). Due to the increasing number of people and objects connected to them, the data generated by these networks are now more diverse and fast. It is now more able to provide organisations with a variety of useful services and products by continuously updating its data at a fast pace (Zhu et al., 2021).

This is because data coming from various sources could take different forms and have multiple implications for organisations that collect them. That's why organisations will need much more effort to be able to reap more valuable insights from such datasets (Maroufkhani et al., 2020). This will also depend on the needs of businesses as to what to collect for their operational and decision-making purposes.

Various sources of data exist, such as social media (including various platforms) and the Internet of Things, transactions within various industries, personal computers and mobile phones and their associated applications and so on (Chen et al., 2014). Big investments from companies such as Google, Amazon, Facebook, and IBM have highlighted the importance of this phenomenon (Chen et al., 2014).

As mentioned earlier, handling such enormous datasets is beyond the capability of a relational database; therefore, new technologies and tools are required to address big data. It is worth noting that technical reviews of big data technologies are not reviewed in this study and are only briefly mentioned. In this regard, Ferraris et al. (2018) refer to three main current technologies available to handle big data as follows:

The Hadoop: Organisations can use Hadoop to process and store their data. The open-source software framework known as Hadoop is designed to allow organisations to process and store large amounts of data efficiently. It can be used to split and distribute large data problems into various sub-problem sets. It then compiles these results into a smaller data set, which is easier to analyse (Ferraris et al., 2018).

NoSQL Databases: This is related to non-relational database systems capable of processing massive amounts of data in a parallel way and supporting various activities such as predictive analytics (Moniruzzaman and Hossain, 2013). A NoSQL database is a type of software that can be used to store and retrieve large amounts of data. It can be designed to handle various types of distributed data by implementing a variety of consistency models. This type of database is designed to solve the performance and scalability issues that arise when dealing with large amounts of data (Liebowitz, 2014).

Parallel analytic databases: These databases provide the ability to analyse and process massive amounts of data in a parallel fashion on several machines at the same time (Ferraris et al., 2018).

Big data and relevant technologies to address them have important implications for organisations. Due to the emergence of new data management trends, such as data visualisation and media, managers are now more likely to adopt these new techniques. According to a survey, over 95% of companies plan on increasing their spending on analytic tools and services in the next couple of years. The demand for related jobs is also expected to grow by 38% by 2023 (Kumar, 2021).

Accordingly, the reports of IBM and big consulting companies such as Accenture and Bain & Company show higher performance as a result of using advanced analytics (Müller et al., 2018). To give another example, despite the complexity of the COVID-19 pandemic, over 90% of companies have maintained their BDA spending at the same level or increased it (Zhu et al., 2021). Those examples show how organisations perceive big data and its significance for their purposes. However, there is scant academic research on the impact of big data on organisational performance (De Camargo Fiorini et al., 2018).

2.3.1. Opportunities brought about by big data

Big data has created various challenges and opportunities for organisations. For instance, companies that have a high rate of use of analytics tend to perform better (Müller et al., 2018). Most of the time, top performers in various fields, such as financial management, budgeting, and business development, tend to use analytics instead of intuition (Lavalle et al., 2011). Additionally, a review of 180 articles about the challenges and promises of big data by Hilbert (2016:135) reveals that “[t]he advent of big data delivers a cost-effective prospect for improved decision-making in critical development areas such as healthcare, economic productivity and security.” In the same vein, organisations may have adopted big data analytics for various purposes such as marketing purposes (analysing customer behaviours and target marketing) and forecasting into the future (such as predicting prices and trends) (Maroufkhani et al., 2020). In general, adopting big data analytics can make a contribution toward enhancing organisational performance ameliorating organisational agility and creating business value (Maroufkhani et al., 2020).

Not only can big data influence the overall performance of an organisation, but it could also be influential in various tiers of organisations, from daily operations (upstream to downstream) to strategic decisions (Constantiou and Kallinikos, 2015). Organisations of various sizes from various industries such as retail, healthcare, finance, military, and so on can benefit from it. In addition, its impact is not limited to internal organisational environments. For example, Constantiou and Kallinikos (2015) argue that Big data can help organisations analyse and deal with environmental trends. It can also help them make informed decisions regarding their resources and environment. This is because organisations could be conceptualised as open systems, and they are constantly interacting with their environments. And also, the business environments are becoming increasingly competitive; therefore, it’s crucial for businesses to keep up with the external changes and observe the external and internal environments regularly in order to make the most of opportunities and avoid threats. In addition, they also emphasize that useful information extracted from data can play a significant role in developing strategies such as marketing strategies. However, as big data is generated through radically various social arrangements, this suggests a more cautious approach with regard to its relevance for strategy (Constantiou and Kallinikos, 2015).

2.3.2. Challenges of big data

On the other hand, big data brings challenges as well, such as inadequately trained specialists and shortage of data managers that are capable of decision-making based on analytics (Hilbert, 2016). Despite the significant investment that many organisations have made in big data and artificial intelligence (BDA), they are still struggling to drive business value from their investments. According to a survey conducted by NewVantage Partners LLC. (2021) cited in (Zhu et al., 2021), over 70% of organisations are still experiencing challenges in adopting these technologies. As mentioned before, adopting big data analytics requires changes in various elements of the organisation. And implementing those changes requires resource allocation. For example, for organisations with limited resources such as SMEs, it might be challenging to adopt big data initiatives (Coleman et al., 2016).

Quality of data is another challenge that organisations who are dealing with big data, might face as huge amounts of data are coming from various sources and it is not necessarily accurate (Moorthy et al., 2015; Mikalef et al., 2018). Information technology's rapid emergence and growth have created a huge amount of data that can be collected and stored in an organisation's infrastructure. This data is often used to improve the efficiency of the organisation. Therefore distinguishing between useful and useless information is very important (Moorthy et al., 2015). It is imperative to screen the quality of big data before conducting the analysis stage, as high-quality data is critical in making cognizant decisions (Mikalef et al., 2018).

Another important organisational function which is influenced by big data is decision-making. The current literature is still lacking in the analysis of the ability of organisations to make decisions based on such large amounts of data (Van Knippenberg et al., 2015). In the following sections, decision-making and the impacts of big data on it are reviewed and discussed.

In addition, based on a review of big data research by Kowalczyk and Buxmann (2014b), technological aspects of big data have been covered broadly, but there is little research on the application of data to date that has helped to provide an understanding of how decision-making could be improved in such environments. Furthermore, there is little understanding of the capabilities involved in such dynamic processes (Sharma et al., 2010). Accordingly, Mikalef et al. (2018) highlight there is scant research on the way organisations should change (for example, regarding human skills and configuration of resources) to reap the values of data available to them and embrace the increasing technological innovations.

Leveraging business analytics to take advantage of data to make sense of decisions requires great changes. Those changes will not happen without changing the organisational infrastructures such as leadership, planning, culture, and structure (Bartlett, 2013). According to Heintze and Bretschneider (2000), early studies would suggest that organisational structure is significantly affected by IT adoption, for example, resulting in their middle managerial layers being decreased. In addition, a reduction in the number of units involved in decision-making processes is another impact of using IT on organisational structure (Downs, 1967). However, recent studies such as that of Slinger and Morrison (2014) argue that applying big data would result in flexible resource allocation, change in sources of influence and location of decisions. Generally, the result of their study showed that big data would affect organisational structure rather than design. They studied the impact of characteristics of big data on organisational structure and design. For example, they found out that volume has a potential impact on the structure by changing the products and services (for example, by crowdsourcing ideas for changes in products or services); variety might have an influence on the allocation of people to various roles or could influence the number of roles. This is mainly because data used to be used to assess individual performance, but now it can be used for analysing large groups.

In general, the rise of social interactions has created an explosion of new ways for people to connect and share information. Some of these include online relationships, feedback, and information sharing. Social networks such as Facebook, Twitter, and YouTube allow users to exchange vast amounts of data. The rise of the internet has created an opportunity for organisations to collect a considerable amount of data. Every new generation of devices has created a vast amount of sensor data. This data can be used to analyse and improve the operations of their businesses. Some of the data collected include user transaction logs, sales logs, and video streaming.

Due to the increasing amount of data collected and transformed into useful information, there has been a huge demand for professionals in the areas of data analysis and data transformation (Mikalef et al., 2018; Constantiou and Kallinikos, 2015). These individuals can help organisations create models and extract patterns and features from the data. Big data has created various fields such as deep learning, machine learning, and artificial intelligence. These technologies allow organisations to analyse and improve the operations of their businesses by identifying patterns and making recommendations (Maroufkhani et al., 2020). For instance, machines can understand the meaning of texts by using artificial intelligence and machine learning (Kune et al., 2016). Therefore, according to the reviews in this part, the following sections of the literature review focus on the organisational decision-making and various elements of the organisational structure and infrastructure to review how they are influenced by big data, as well as the dynamic capabilities that could be developed or modified to facilitate the utilisation of big data.

2.4. Organisational design and structure

This section is dedicated to organisational design and structure. This is because advanced information processing mechanisms seem to be closely linked to the organisational structure as the information flows within the structure, and organisational design could facilitate or hinder the information flow.

“Organisational structure is the formal system of task and authority relationships that control how people coordinate their actions and use resources to achieve organizational goals”(G. R. Jones, 2013:30). However, Organisational design refers to the ways of balancing various elements of organisational structure (Cunliffe, 2008).

According to Figure 2-3, various elements and aspects of organisational structure are managed by means of organisational design. In other words, the organisational design allows firms to deal with dynamic environments by redesigning and transforming the structure, and also balancing the need of them in managing either internal or external pressures.

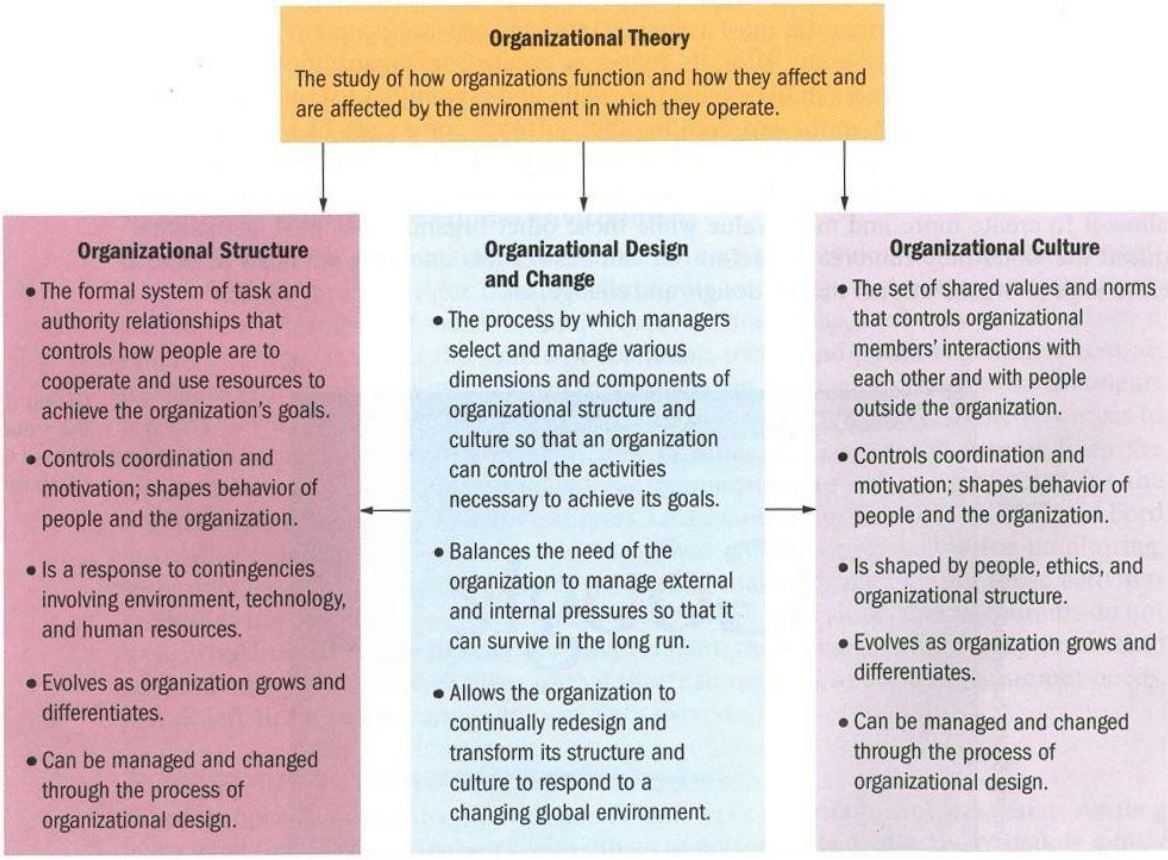

Figure 2-3: The relationship among organisational theory, organisational structure, culture, design, and change (G. R. Jones, 2013:30)

Anand and Daft (2007b) refer to three different eras of organisational design as follows: the first era, which was dominant till the 1970s, included self-contained designs with a vertical command chain and clear boundaries of organisations. Some of the main designs of this era were functional, divisions and matrix designs that relied heavily on vertical hierarchies and command chains. Experiencing the limits of traditional designs as business environments were becoming more complex, the second era started in the 1980s focusing on team and processes-based designs such as horizontal designs with a flattened hierarchy. Meanwhile, advances in information, communication, and network technologies shifted organisations' information processing capacity, and they felt the need to reshape the internal coordination and communication structures. This horizontal design decentralised decision-making and empowered employees, which facilitated learning, so internal processes could be managed more effectively and, therefore, responsiveness to environmental stimuli increased. The mid-1990s experienced the third era of designs on account of significant advances in technologies, the internet and emerging economies shaping the design of hollow organisations. Those fast-changing shifts and the emergence of skilled expertise made organisations aware of the fact that it was difficult to keep pace with dramatic changes, so they opened up the organisational boundaries for example, by outsourcing some specific tasks (outsourcing non-core business processes). Modular organisations were also one the popular designs of this era, as it is obvious from its name, composed of various modules capable of being hived off when necessary. Unlike hollow designs, modular designs tend to outsource pieces of the product rather than the process itself. Virtual companies are another type of design within the last era which is formed as a result of joint ventures or collaborations. This design is very common in high-technology industries, as two companies might decide to collaborate to take advantage of the exceptional opportunities in the market by bringing their domain of excellence and linking people, assets or ideas (Anand and Daft, 2007a).

Organisational design plays an important role in regulating information flow within organisations. Earlier studies, such as those of Lewis and Fandt (1989), point out the importance of effective information processing and disseminating it to decision-makers. Accordingly, they studied the various factors that might influence the information searching behaviour by managers affecting their quality of decisions. One of the significant factors in directing the flow of information is the internal design of organisations (Lewis and Fandt, 1989). They refer to two types of organisational design suggested by Burns and Stalker (1961), including mechanistic and organic designs. The first one could be characterised as more bureaucratic with a vertical line of communication, higher job specialisation, and rigid and closed structure, whereas the latter one is more flexible with open structure, high task uncertainty, and lateral and vertical communication networks (Lewis and Fandt, 1989). Therefore, out of the aforementioned types of structures, mechanistic designs would be more effective in stable environmental conditions, whereas organic designs provide better information flow, less rigid and more adaptable internal systems, and flexibility in dynamic conditions (Lewis and Fandt, 1989). In this sense, Curado (2006) argues that organic designs might be more appropriate for enhancing organisational learning associated with less centralisation and formalisation. Accordingly, Csaszar (2013), in his study about the determinants of exploration and exploitation, highlights that mechanistic designs are more concerned with exploitation compared to organic designs which facilitate exploration. Although the above-mentioned designs are still relevant, conditions of recent markets which increasingly experience changes regarding technology, global competition and social demography, would require more open forms with porous boundaries (Felin and Powell, 2016).

Kennedy (1994) studied the difference between parallel and serial structures in terms of information processing, concluding that serial structures ordered by ability would be beneficial if communication costs are less, whereas parallel structures might outweigh the serial structure if communication costs are higher. Therefore, optimal structure regarding information processing depends upon the trade-off between specialisation in serial and fewer communication costs in parallel structures (Kennedy, 1994).

The organisational structure is not solely limited to defining the relationship between different parts of the organisation but is also about features in support of the structure, culture, the system within which it operates, and resources, referring to the coordination of organisational processes (Verle et al., 2014). On account of contemporary dynamic environments and ever-increasing advances in technologies and competition, organisational structures are evolving into more flexible and adaptable forms with more horizontal and decentralised structures compared to traditional mechanistic ones (Verle et al., 2014). For example, Weigelt and Miller (2013) argue unit autonomy would contribute to integration and firms' adaptation to changes being occurred as a result of knowledge-intensive tasks.

Designing or redesigning an organisational structure is not a straightforward process. In this sense, Jones (2013) refers to four design challenges that need to be dealt with during organisational design processes. The principal one is differentiation related to the allocation of people and resources to specific tasks and therefore establishing authority relations. It concerns the level of vertical or horizontal differentiation, which provides the organisation with the ability to control specific activities (G. R. Jones, 2013). The second challenge is associated with balancing differentiation and integration and choosing the proper integration mechanism. The third is concerned with the level of centralisation and balancing it. The fourth is related to standardisation and the appropriate amounts of formalisation and socialisation (G. R. Jones, 2013).

This study draws on the decision-making paradigm of organisational design. Huber and McDaniel (Huber and Mcdaniel, 1986) argue there are different approaches to the organisational design, of which the earliest one is the "*political paradigm*", focusing on allocating power-enhancing resources to individuals who are likely to be more loyal and supportive. Next is the "*accountability/authority paradigm*", which is concerned with allocating responsibilities to people who are accountable for fulfilling them. The industrial revolution was followed by the third paradigm, which primarily focuses on the flow of work. Structure and processes should be designed in a way that facilitates the operations and processes of production in organisations. The fourth paradigm is called the "*decision-making paradigm*". This paradigm basically concentrates on the concept that organisational structure and processes should be designed in a way that facilitates decision-making. In this sense, organisations with high-quality decisions are deemed effective organisations. They also argue that the reason for emerging the fourth paradigm can be the upcoming nature of the changes in decision-making processes and increasingly dynamic environments. Therefore, on the ground that changes in organisational processes are contingent upon changes in structure, the last paradigm focuses on the structures that facilitate decision-making. Additionally, the main concept of the paradigm is considering the information sources because information channels are deemed as core components of any organisational design (Huber and Mcdaniel, 1986).

Huber (1990) argues that advanced information technologies would affect organisational design and structure because of their particular characteristics. Those changes are made by means of facilitating individual and organisational communication in a less expensive and faster way, controlling participation and access in communications more precisely, facilitating storing and retrieving huge amounts of information, and also combining and reconfiguring information more accurately resulting in the creation of new information (Huber, 1990). Additionally, those changes might be on subunit structures and processes, organisational memory, or organisational structure and processes. For example, drawing on the works of Galbraith (1973) and

Thompson (1967), Sor (2004), by studying a few cases, concluded that computer-based systems could absorb tasks, resulting in more simplified structures and reduced task interdependencies.

In terms of design in knowledge-intensive industries, actor-oriented organisations seem to be more effective in dealing with such environments (Snow et al., 2017). Accordingly, Snow et al. (2017) refer to three important elements of actor-oriented designs as follows: "actors" whose activities are based on self-organising and collaboration, "Commons" includes necessary resources provided for actors such as knowledge and databases, "protocols, processes and infrastructures" in which protocols lead the way actors behave, a combination of processes result in an agile organisation, and infrastructures contribute to connecting people. It is important to note that actors can be made up of people, teams or even firms that have certain capabilities and awareness of the processes and structure of their organisation to operate autonomously. Situation awareness is another influential aspect of Commons as "When actors share an up-to-date awareness of the organization's situation, everybody in the organization can make the right decision or take the correct action without seeking direction or authorization from the hierarchy." (Snow et al., 2017:6). Felin and Powell (2016) highlight the role of individual characteristics (in polyarchic designs) in building higher-order capabilities to sense the environmental signals as they work together towards the collective enterprise. Accordingly, they believe porous boundaries of organisations would facilitate information flow either from inside to the environment and the way around.

Galbraith (2012) considers big data as a strategic dimension with significant organisational design implications, though a big challenge in organisational design. Flexible resource allocation is one of the consequences of big data on account of effective monitoring of the supply and demand, and consequently moving capital, employees and related sources (Slinger and Morrison, 2014). As big data can be an important external source of knowledge, particularly for organisational learning purposes, understanding design implications regarding knowledge management and learning would be useful.

In terms of knowledge management, Foss et al. (2013) studied the role of organisational design in external knowledge exploitation, highlighting the important character of the interaction with external parties such as customers, partners, and suppliers. They consider the delegation of decision authorities as an important factor in facilitating the exploitation of new knowledge. However, regardless of the benefits of decentralisation in knowledge exploitation, there might appear to be some issues regarding the coordination of actions taken. This is because knowledge transfer might become easier but how to share it with other sections in need of it might be challenging. Additionally, decentralisation by itself would not be enough to absorb external knowledge, and complementary practices to encourage this process would be needed such as communication channels and incentives (coordination devices).

Regarding organisational learning, Benavides Espinosa and Merigó Lindahl (2016) argue that whereas organic structures with less formalisation and decentralised decision-making processes would facilitate learning, mechanistic structures would not hinder learning in larger organisations. This is because there are different factors such as "[…]knowledge, procedures, tasks, technologies, and even products or business transactions from which firms can learn. In addition, "the typology of problems the organization must solve is much larger, which creates more opportunities for learning" (Benavides Espinosa and Merigó Lindahl, 2016:1344). Additionally, Felin and Powell (2016) argue optimal designs for Dynamic Capabilities (DCs) in response to a dynamic environment would be highly integrated and differentiated designs. This is because in minimally integrated and differentiated, one's information would not be adequate. In addition, if only integration is high, innovation would be stifled and in designs with only high differentiation, innovation would be misdirected (Felin and Powell, 2016).

According to the literature review conducted by Sharma et al. (2010), the contribution of business analytics towards performance gains and competitive advantage has been studied broadly, but organisational structures, processes and capabilities required to do so, are not clear and are still to be studied. They argue that the ability to capture those advantages depends upon a dynamic business analytics capability. Specifically, this type of dynamic capability is concerned with developing and implementing competitive actions by utilising information assets at either the organisational or the operational levels. Given the above-mentioned arguments, and on the ground that there does not exist a well-developed theory in this area, in-depth case studies are required to understand mechanisms and causal relationships (Sharma et al., 2010).

The rapid emergence and evolution of new business organisations over the past century have led to a shift in how they structure and function. Instead of focusing on hierarchy, they emphasise the importance of people being able to take on multiple tasks and responsibilities (Snow et al., 2017). The focus of today's organisations is on improving the speed and accuracy of their decisions by using data and analysis. They are also more aware of the changes in consumer attitudes and culture. They use social media to connect with their customers and demonstrate their willingness to listen to them. They also understand the importance of technology in their operations and are more likely to adopt it as a part of their strategy. To be considered a digital firm, organisations and businesses need to demonstrate these characteristics (Laudon and Laudon, 2020).

Having reviewed the organisational design and structure, various forms of structures, their advantages and disadvantages, and their implications for organisatoins and information processing mechanisms, the following section aims to review the literature on organisational decision-making.

2.5. Decision making

This section is dedicated to reviewing organisational decision-making. Accordingly, various decision-making styles and challenges organisational decision-making are plagued with, and the role of information and knowledge are discussed within this section.

In today’s business world, many managers rely on information to make decisions. They don't necessarily have access to the correct information to make informed decisions and improve their performance. This can lead to underinvestment in goods and services, poor response times, and misallocation of resources (Laudon and Laudon, 2020). In addition to raising costs, these poor decisions can also lead to customers losing their confidence. In the past ten years, the rise of technology has allowed managers to make more informed decisions by allowing them to access real-time data from the market. For instance, Privi, an Indian company that manufactures and supplies aroma chemicals, uses a software system from Oracle to analyse and monitor the performance of its employees. The software system helps managers make faster decisions by integrating their employee records. It allows them to review and analyse employee performance ratings, and it also allows them to monitor the hiring status of their employees. A digital dashboard helps them view and monitor the various aspects of their organisation's operations (Laudon and Laudon, 2020).

A decision-making process is a mental process that enables individuals to achieve specific goals (Intezari and Pauleen, 2017). A decision-making process is a managerial activity that involves assessing the various options available to achieve the desired outcome (Intezari and Pauleen, 2017). According to Fulop (2005), a decision-making process can be described as a psychological process in which an individual tries to achieve goals by minimizing risks and using fewer resources.

There are various approaches to making decisions at the individual and organisational levels. There are two main types of models that are commonly used in this type of decision-making: rational and non-rational (Dane and Pratt, 2007). The aforementioned decision-making styles have been at the centre of debates for a long time and are still alive and relevant (Bullini Orlandi and Pierce, 2019).

2.5.1. Normative decision making

Rational or normative decision-making style is one of the main approaches, as mentioned earlier. Each of the approaches has its own support as a proper information processing and decision-making style, as Dane and Pratt (2007) believe that Rational decision-making is a process that draws upon the evidence and logic of a given situation to arrive at a reasonable outcome. This is done through the evaluation of data and the application of relevant information. In other words, this logical process results in sensible outcomes. According to Fulop (2005), rational decision-making could be grouped into eight steps as follows:

1. Problem defining: A problem definition is a process that helps a decision maker identify a problem's complexity and develop a strategy to solve it. It helps them manage the problem in a more manageable manner.

2. Determination of requirements: The definition of requirements involves identifying the various constraints that could prevent the project from achieving its goals.
3. Objective setting: this stage entails defining optimal goals.
4. Determining alternatives: The goal of determining alternatives is to identify the possible solutions that could meet the project's objectives.
5. Criteria defining: The next step involves defining the criteria that will help the decision maker identify the ideal alternatives.
6. Choosing a decision-making tool: The next step is to choose the appropriate decision-making tool. This tool will help the decision-maker analyse the various options available to address the issue.
7. Evaluation of alternatives: The evaluation phase involves ranking the various alternatives against the established criteria.
8. Solution validation: The solution validation phase involves validating the alternatives' viability and success.

2.5.2. Intuitive decision making

The difference between a rational decision-making style and a non-rational one is that the former relies on the perception of the issue by the decision-maker, while the latter relies on their experience. Most decision-makers tend to assimilate the various concepts of different approaches at the same time instead of following a single approach. Holzinger (2014) argued that heuristics are very important in decision-making because they help speed up the process of dealing with problems. In this model, intuition and experience play an important role rather than evidence (Oliveira, 2007). However, Dane and Pratt (2007) argued that decision-making models that rely on heuristics could potentially affect the evaluation of courses of action and solutions to complex problems. Nyström (1974) also argues that different cognitive styles of decision-making (analytical versus intuitive) at the individual level would affect the organisational level decision-making with respect to information collecting and processing because those cognitive approaches would guide the type of information being sought and processed.

According to Jones (2002), one of the alternative approaches to rational decision-making is bounded rationality which includes four particular principles as follows:

1. Intended rationality: The intention of a decision-maker is more important than the actions that he or she takes.
2. Adaptation: this stage is concerned with how decision-makers adapt to their environment and learn from it.
3. Uncertainty: Uncertainty can affect the choices that a decision-maker makes. This is because there is not enough information about the various factors that affect a decision.
4. Trade-offs: this stage is concerned with evaluating different options in terms of limitations and time.

It is important to note that the above-mentioned debate has evolved during the time on account of an exponential increase in the data and information and related tools for data analysis available to managers making information processing easier and faster than before. Therefore, the interest in this specific style of information processing is increasing (Bullini Orlandi and Pierce, 2019). For example, Bullini Orlandi and Pierce (2019) conducted a study on reframing decision-making styles in technological settings, comparing analytical and intuitive information-processing styles. They found out that because of the nature of location-sensitive and real-time data coming from customers, an analytical style of decision-making would be more useful in this setting. However, their results support the idea of naturalistic decision-making as a combination of either of those mentioned processes at the same time resulting in more effective decision-making. Accordingly, Simon (1987:63) believes that “The effective manager does not have the luxury of choosing between ‘analytic’ and ‘intuitive’ approaches to problems”. Nyström (1974) believe normative and descriptive approaches complement each other rather than competing in uncertain conditions. In this setting, he refers to the important role of information in reducing uncertainty; however, the provided information is not necessarily correct and relevant to the subject matter, so it might increase the uncertainty.

Organisational decision-making has been plagued by various challenges such as uncertainty, complexity and equivocality (Choo, 1991; Herbert A Simon, 1982). Uncertainty refers to a situation in which adequate information about the various alternatives and their consequences does not exist and results in the decision-making process being more difficult (Choo, 1991). Complexity refers to an abundance of variables or elements which result in taxing human cognitive capabilities (Jarrahi, 2018). Equivocality is considered as a situation where different and divergent interpretations about the decision exist at the same time, coming from a conflict of interests of parties involved in the decision domain (Weick and Roberts, 1993). Therefore, due to the complexity of today's decision-making environment, it is often difficult to make informed decisions. This is why it is important that decision-makers have the necessary resources to quickly find and analyse the information they need. (Burstein and Holsapple, 2008). Jones (2002) states that existing knowledge and the information that is provided externally are very important factors that decision-makers consider when making decisions. Accordingly, Klein (2008) believes that making decisions in a naturalistic manner requires a decision-maker to be able to quickly find, analyse, and integrate various sources of information.

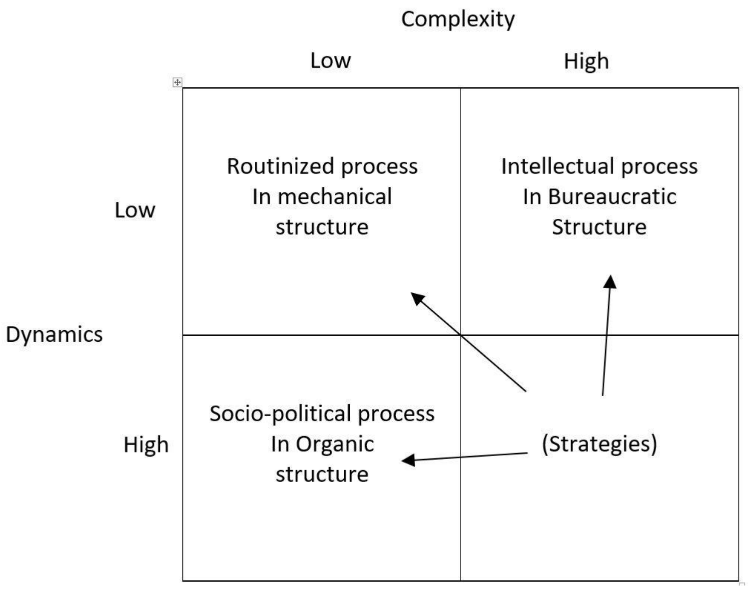

Figure 2-4: Rational model of organisational decision-making adapted from Axelsson and Rosenberg (1979:48)

According to Figure 2-4, Axelsson and Rosenberg (1979) refer to four types of organisational issues in which complexity reflects the abundance of situational factors, and dynamics reflects the variability of those factors. Accordingly, structures and processes suitable to deal with such issues are briefly mentioned in the table. In a situation associated with high complexity and a high level of dynamism, dealing with such issues would require both intellectual processes with bureaucratic structures and socio-political with organic structures simultaneously. Therefore, as possession of two mentioned structures and processes may not be possible at the same time, those issues are usually converted into other types through various strategies such as contracting and vertical or lateral coordination (Axelsson and Rosenberg, 1979). However, simplification and stabilisation of issues by a high degree of complexity and dynamism are becoming more difficult on account of exponentially increasing environmental changes in modern societies over which organisations have no or little control.

Decision makers have a limited information processing capacity, and organisational structure could be considered an optimal response to it (Kennedy, 1994). Kennedy (1994) argues that technological improvements might result in substituting human information processing with technology information processing, but it does not necessarily mean that optimal structure should be less hierarchical. In this regard, he suggest that “the trade-off between specialization and communication requirements is an important determinant of the structure of organization” (Kennedy, 1994:48). According to Huber (1990), advanced information technology would enhance the availability of information and consequently might result in organisational design change; therefore, the effectiveness of decision-making would increase. Information and data play an important role in decision-making, which is why Simon's decision model (1959) is an ideal example. It involves three steps: intelligence, design, and choice. The first step in the process involves gathering and evaluating information from various sources to achieve a specific goal.

Berry (2006) studied the impact of computer-mediated communication on organisational decision-making, team processes and communication by examining the 25 years of literature on business communication and management. In this sense, he refers to the advantages and drawbacks of team decision-making processes. On the one hand, teams are more effective with respect to decision qualities as they are able to process a greater amount of information and they are made up of diverse expertise, creating a synergetic effect by criticising and amplifying each other’s ideas. For example, board diversity is favourable as it brings various skills to the table (Kakabadse et al., 2018). In addition, according to Kakabadse et al. (2018) boards who are capable of teamwork would contribute to value creation significantly. On the other hand, team processes are believed to be time-consuming as members have to have face to face meetings or have other drawbacks such as minority domination and social pressures (Berry, 2006). Computer-mediated communication channels would facilitate information sharing regardless of the geography, time zone and the number of participants, creating more flexibility and effectiveness (Berry, 2006).

Fredrickson (1986) argues that organisational structure as a whole would influence strategic decision-making processes. This is because strategic decisions are not made solely by one person and more importantly, they are not made outside the dominant structure. He believes that choice is one of the steps in decision-making processes meaning that there are other factors involved, such as information seeking and other members’ contributions from various tiers of the organisation. In terms of the role of structure, Fredrickson (1986) discusses the role of structural elements including centralisation, formalisation and complexity. Centralisation might contribute to strong coordination of decisions but obviously would tax decision makers' cognitive capacities at higher levels. Formalisation, which shapes the members' behaviours, would shape the ways they perform specific tasks subsequently limiting their decision-making freely. A higher level of complexity, referring to interrelated vertical and lateral differentiation and dispersion, would affect the level of coordination and control over decision-making activities. Therefore, various elements of the organisational structure have important implications regarding strategic decision-making processes.

Eisenhardt (1999) highlights several fundamental elements with respect to enhancing strategic decision-making as follows: to be able to spot opportunities and threats in an accurate and timely manner, frequent meetings to establish collective intuition would be useful. Gathering diverse teams and provoking various ideas causing a quick conflict, would improve the decision qualities. Discipline, timing and consensus with qualifications would contribute to the momentum of choices. Additionally, as there might be conflicts during the decision-making processes, stressing the common goals and having fun can defuse politics. Compared to the traditional concept of strategic decision-making, which is usually concerned with building the long-term position of the firms, Steptoe-Warren et al. (2011) state it is more about adaptation and improvement which is continuous, evolving to confound competitors and takes into account the environmental factors. Accordingly, with respect to strategic thinking, they emphasise the key part of external factors in conjunction with internal information and middle managers in establishing strategies to determine whether choices are operational.

Huber (2003) explains the characteristics of future business environments and the way in which organisational decision-making may evolve in such situations. As decision loads will increase, in order not to decrease the decision performance, decision-making units will have to be increased, and the efficiency of decision processes should be enhanced (for example, by reducing the number of cases which require a great deal of analysis). In order to cope with multidimensional decision situations as a result of environmental complexity, Huber suggests two main approaches. First is enhancing the knowledge and mental models of individuals who make decisions through various processes such as training. The second approach is also concerned with learning and possession of knowledge of various kinds in case of facing more complex issues, implying that broader scope of decisions would help decision units to learn and consequently, more individuals will involve in decision-making processes.

Meanwhile, Huber (2003) argues that increasing competitiveness has two important implications with respect to organisational decision-making. Because of the existence of numerous and agile competitors, late decisions and mistakes might be catastrophic as competitors can take advantage of those mistakes quickly. The second one is associated with the accumulative impact of small losses or gains in relative performance that might result in a firm or a competitor being pushed out of the saturated market.

2.5.3. Role of knowledge management in decision-making processes

Mckenzie et al. (2011) highlight the crucial role of knowledge management, which is subject to individual and organisational learning capacity, in developing fast decision-making processes. Accordingly, developing such capabilities to make sound decisions depends upon different factors in which increasing reflection and increasing awareness are of high significance (Mckenzie et al., 2011). There are various factors involved in enabling, expediting and facilitating knowledge management processes. Accordingly, Abubakar et al. (2017) refer to three main KM enablers as structure, culture and technology. Abubakar et al. (2017) argue that organisational members with "T-shaped" skills, which refers to individuals' abilities to have deep knowledge of their own discipline and collaborate with other parts of the organisation to gain and create new knowledge, would facilitate the knowledge creation process. Another key element is collaboration and the quality of interaction between members. In this regard, the vital role of information technologies should not be overlooked as a knowledge sharing and creating facilitator. Furthermore, they highlight the important role of organisational learning in knowledge creation processes (Abubakar et al., 2017).

"Distinguishing different types of decision-making provides a sense of different knowledge and learning requirements for each context." (Mckenzie et al., 2011:406). Thus, specifying decisions of various kinds would be helpful with respect to establishing appropriate learning and response strategies to address them. According to Mckenzie et al. (2011), decision contexts can be classified into three primaries and two special groups as follows:

- Tactical issues: this type accounts for the most frequent types, including simple decisions that cause and effect links are clear, and outcomes can be predicted.
- Operational issues: compared to tactical issues, this type is less frequent, though with identifiable cause and effect links, requiring experts to handle the situation, as they are more complex.
- Strategic issues: they include complex issues with no right answer, cause and effect linkages, and predictable outcomes because they encompass interconnected factors and influences.
- Special issue 1: “crisis or emergency” with higher risk requiring a quick response. Continuous re-evaluation and re-diagnosis are required in a timely manner to handle the situation.
- Special issue 2: most profound issues, such as questioning the identity of the organisation, lies in this group requiring different kinds of knowledge and learning to address which willingness to “learning and unlearning” processes are important.

Internal and external collaborations with partners would enhance access to knowledge by filling the knowledge gaps, providing access to experts from outside the organisations at a less expensive cost, and keeping the knowledge relevant (Mckenzie et al., 2011). Boulesnane and Bouzidi (2013) refer to the three important organisational capabilities in facilitating decision-making. First is the intelligence collective, which is concerned with the collaboration of individuals and solving problems in groups creating synergy and exceeding individual decision-making. Second is knowledge management related to collecting, storing, and facilitating dissemination and communication of explicit and implicit knowledge. “Finally, innovation is the exploitation of ideas, products and resources allowing the achievement of higher levels of organizational productivity and growth” (Boulesnane and Bouzidi, 2013:389). Accordingly, advanced information technologies could contribute to mediating the relationship between the mentioned concepts and decision-making activities. It is also important to note that those concepts are interrelated (Boulesnane and Bouzidi, 2013).

Mckenzie et al. (2011) developed a framework to improve dynamic decision-making. This framework contains three important elements including human capital, structural capital, and relational capital. Human capital is concerned with individual learning, developing and retaining experts; structural capital refers to the use of technology in structuring, accessing and integrating explicit sources of knowledge; relational capital is associated with internal and external collaboration, which requires an integrated approach.

One of the underlying elements of managerial capabilities is human capital which is based on past experiences, and the other driver is social capital referring to social relations and networking, which facilitate the flow of information and experience; the last driver is managerial cognition which serves as a basis for making decisions (Mckenzie et al., 2011). Managerial cognition refers to the managerial mental models and beliefs shaped over time, based on experience and would determine the information processing model (Mckenzie et al., 2011). Individuals abilities are a result of interaction between their life experiences and their innate abilities, so this would make every person unique as everyone passes through different life experiences (Beck and Wiersema, 2013). These elements all together have an influence on strategic decision-making by impacting resource configuration and orchestration (Beck and Wiersema, 2013). Maitland and Sammartino (2015) argue that decision-makers perceive the same environmental situation differently on account of the various cognitive resources they bring to decision processes which have been built based on their experiences. They argue that heuristics can be used as a powerful tool in high-stake and dynamic conditions. Kunc and Morecroft (2010) consider resource conceptualisation as the first step in decision-making according to the RBV approach. Highlighting the dynamic managerial capabilities, they argue that managers' mental models and cognitive capacities based on various knowledge and experience they have would influence the way of their perception of the industry and consequently resource allocation. Laureiro-Martínez and Brusoni (2018) studied cognitive flexibility in overcoming cognitive inertia in facing unprecedented and changing organisations considering cognitive flexibility as a key antecedent of individual decision-making when facing problems of various kinds.

In this section, existing literature on organisational decision-making was reviewed. According to the discussions, there are various elements involved in making organisational decision-making more effective.

On the individual level, decision-makers might resort to different decision-making styles such as normative, intuitive or naturalistic. It seems that the individuals' perception of the issues plays a role in determining the decision-making style. The perception seems to be shaped based on the individuals' experience and cognitive capacity (Mckenzie et al., 2011). Another influential factor in determining the decision style is access to information, as related analytical tools available to managers are making information processing easier and faster than before (Beck and Wiersema, 2013). It is worth noting that individual decision-making styles would influence organisational decisions as peoples' cognitive approaches will determine the types of information to be sought and processes to be developed.

On the organisational level, uncertainty, complexity and equivocality seem to be among the challenging factors. Mitigating those issues requires appropriate information processing mechanisms and access to timely information. As discussed, decision-makers have a limited information processing capacity, and organisational structure could be considered as an optimal response to it (Fredrickson, 1986). But this does not necessarily mean there is one best structure that organisations can adopt in order to facilitate the information flow. In order to cope with multidimensional decision situations as a result of environmental complexity, knowledge management seems to be an effective tool which is subject to individual and organisational learning capacity (Mckenzie et al., 2011; Abubakar et al., 2017).

Some of the significant factors in enabling, expediting and facilitating knowledge management processes that would result in more appropriate decisions are:

- Enhancing the knowledge and mental models of individuals who make decisions through various processes such as training, developing and retaining experts (Mckenzie et al., 2011; Abubakar et al., 2017).

- Organisational structure which is responsible for facilitating internal and external collaboration and communication between organisational members which results in better information flow and learning (Fredrickson, 1986).
- Organisation culture which shapes the members' behaviour within the organisation. For example, having an analytical culture within the organisation would result in trust in the insights that emerged from the data for decision-making purposes (Frisk and Bannister, 2017).
- Technology and analytical tool at managers' disposal would result in better and faster access to information required for decisions which result in uncertainty reduction (Maroufkhani et al., 2020). This would also facilitate communication between organisational members.

As mentioned in the previous sections, the emergence of big data has significantly contributed to access to a deluge of information and made business environments dynamic. Organisations need to develop new capabilities or reconfigure the existing ones in order to be able to make fast and timely decisions. The following section reviews the dynamic capabilities approach and its importance for organisations to cope with changes in the big data era.

2.6. Dynamic Capabilities (DC)

This section reviews the concept of dynamic capabilities as an important approach for organisations how to cope with changing environments. Therefore this section is dedicated to defining dynamic capabilities and how organisations can develop those capabilities in the big data era. Some of the relevant concepts such as managers' role, knowledge management and organisational learning, leadership, talent management and Human Resources (HR), organisational culture, and organisational design, and their role in developing dynamic capabilities, have also been discussed in this section. Even more, various management theories used in the study of big data have been mentioned and the rationale for selecting dynamic capabilities as a theoretical lens has also been discussed.

The difference between resources and capabilities might be confusing; therefore, it is worth noting the difference between resources and capabilities, as Johnson (2019) states:

“Resources are the assets that organisations have or can call upon, and capabilities are the ways in which those assets are deployed. A shorthand way of thinking of this distinction is that resources are what we have (nouns) and capabilities are what we do (verbs). Other terms are sometimes used, for example capabilities and competencies are often used interchangeably (earlier editions of this text used the term competencies for capabilities).” (G. Johnson, 2019:137).

In this sense, as big data is capable of providing organisations with an important intangible resource which is information and the insights extracted from the data (Maroufkhani et al., 2020), organisations need to develop the necessary capabilities in order to be able to take advantage of this invaluable resource. Additionally, as mentioned in the previous sections, big data contributes to making corporate environments highly dynamic, so coping with those changes would also require developing dynamic capabilities.

The concept of dynamic capabilities was a buzzword during the 1990s when it came to learning and developing new skills (capabilities and dexterities). This concept was often accompanied by existing resources (Barney, 1991; Teece et al., 1990). According to Bowman and Ambrosini (2009), this concept is a framework that aims to develop a resource-based view of an organisation's capabilities and resources. It involves identifying and developing processes that can help improve the organisation's competitive advantage by changing the organisation’s resources (Ambrosini and Bowman, 2009).

There is a danger that competitive advantages can be lost to competitors due to the lack of change in the environment and the lack of resources and capabilities that were the basis of their success. This is why it is important that the resources and capabilities that were used to achieve competitive success are continuously updated. A dynamic capability is a type of capability that can be used to achieve a specific strategic change. It can be used to create or extend an organisation's current capabilities (Whittington et al., 2019). For instance, a new product development process can be carried out using a dynamic capability. A dynamic capability can also be used to develop and implement various management and recruitment processes. These can be carried out through the establishment of formal organisational systems, such as mergers and acquisitions (Whittington et al., 2019). There has been significant research and advances in the dynamic capabilities approach since it emerged. However, there is still room for research in terms of understanding to what extent DCs are context-specific or generic and also how they can integrate with other research fields (Ambrosini and Bowman, 2009)

Sensing, Seizing, and Reconfiguring, according to Teece et al. (1999), are among the three generic types of dynamic capabilities. The concept of sense refers to the continuous search for and exploring new opportunities in various markets and technologies. This process can involve conducting research and development activities to identify and develop new products and services. For instance, according to Whittington et al. (2019), Microsoft was able to identify the threats and opportunities that emerged in the cloud computing and tablet markets. After identifying and addressing the potential opportunities that exist in a market, a company must then seize the opportunity through its various processes and activities. For instance, by launching its own cloud computing services and tablets, Microsoft was able to capitalise on the growing demand for these products. The ability to seize an opportunity requires the reevaluation and reconfiguration of an organisation's capabilities and investments in order to capitalise on new opportunities. For instance, Microsoft had to make significant changes to its existing hardware and software capabilities in order to accommodate the growing popularity of tablets and cloud computing (Whittington et al., 2019).

On the ground that decision-making is a central managerial activity and managers play an important role in resource orchestration within organisations, the following section discusses the key role of managers in developing DCs. The characteristics of dynamic capabilities are likely to be related to people's behaviour within an organisation, as Teece (2007) considers as “micro foundations” of dynamic capabilities. These include the way in which decisions are made and the importance of personal relationships. In addition to these, other factors such as organisational processes and beliefs are also taken into account to evaluate the effectiveness of the capabilities.

In the DC approach, managers have an important role in terms of designing the competitive position of their organisations (Kor and Mesko, 2013). This process involves identifying new trends and favourable circumstances and coming up with new ideas with the help of existing knowledge. “Even the best-designed dynamic capabilities, however, cannot succeed without seasoned managerial judgement ” (Day and Schoemaker, 2016:75). However, The literature on dynamic capabilities does not provide a comprehensive understanding of the various managerial capabilities that are involved in the development and implementation of resources (Kor and Mesko, 2013). The management team's role in developing and implementing dynamic capabilities is one of the most critical factors that can be considered when it comes to enhancing a company's performance in terms of sensing opportunities and changes and responding to them appropriately (Ambrosini and Bowman, 2009). In this regard, The extent to which managers are able to interpret and perceive changes and issues is very important in making decisions (Aragón-Correa and Sharma, 2003).

Dynamic managerial capabilities are among the key factors influencing the ability of organisations to fit their competencies with external conditions. Ander and Helfat (2003) categorise dynamic managerial capabilities into three concepts: managerial human capital, social capital and cognition. The interactions that managers have with other people develop managerial cognition. This is a part of their professional and personal experiences that helps them make better decisions. However, all three mentioned aspects are interconnected. For example, interacting with other people outside of an organisation can help managers gain a deeper understanding of their problems and improve their decisions (Kor and Mesko, 2013).

Having discussed the managerial and organisational dynamic capabilities, the role of information in this sense needs to be specified. Information extracted from data is deemed one of the most significant organisational resources (Samuel Fosso Wamba et al., 2017). Accordingly, Wamba et al. (2017) consider big data analytics as a dynamic capability and argue it is becoming more prevalent in today's competitive environment as organisations look to improve their decision-making capabilities and reduce their risk of failure. To achieve this, they need to adopt a more effective and efficient approach to managing their data. This can be done through the establishment of a framework that enables them to make informed decisions and manage their data through organisational changes in terms of structure, processes and data processing mechanisms (Kowalczyk and Buxmann, 2014a). It seems that strategic use of dynamic capabilities, as some intellectual dexterities and organisational processes depend upon data flows in organisations (Constantiou and Kallinikos, 2015). The above discussions highlight the link between dynamic capabilities and information flow within organisations. And as big data is the focus of this study, it is important to review the main theoretical approaches to studying big data initiatives.

Braganza et al. (2017) believe that there was little attention given in previous studies to coherent and sustainable processes for establishing big data initiatives. They consider three approaches to developing thinking about big data as follows: dynamic capabilities, RBV (Resource Based View) and Knowledge-Based Views (KBV) of the organisations. On the other hand, Merendino et al. (2018) argue that cognitive capabilities, behavioural factors and dynamic capabilities are interdependent and fit within the KBV approach because they are trying to figure out the antecedents and consequences of knowledge. These capabilities together would enhance the quality of decisions and the capabilities of organisations in sensing and seizing environmental opportunities and avoiding threats (Merendino et al., 2018). Those examples emphasise the importance of dynamic capabilities in studying big data and dynamic decision-making. In this sense, DC approach highlights the key role of managerial decision-making in dealing with dynamic environments.

It is worth noting that various Management theories have been used in the study of big data and its impact on multiple activities and layers of organisations, from supply chain management to market intelligence and organisational performance. De Camargo Fiorini et al. (2018) conducted a literature review about the management theories used in the study of big data, which shows that 19 theories have been used in big data-related research. Table 2-1 summarises them.

Table 2-1: Management theories used in the study of big data (De Camargo Fiorini et al., 2018)

	Management Theory	*Research Focus*
1	Actor-network theory	Investigating the impact of big data on supply chain sustainability (Hazen et al., 2016)
2	Agency theory	Investigating the impact of big data on agency costs (Hazen et al., 2016)
3	Contingency theory	Focusing on the application of big data in adapting to environmental dynamism and verification of those adaptation processes (Waller and Fawcett, 2013)
4	Diffusion of innovation theory	Understanding big data adoption and adoption of technologies and innovations (Rogers, 2010)
5	Dynamic capabilities	Concerning developing new capabilities or reconfiguring the existing capabilities through big data analytics to cope with the changing environment (Grindley and Teece, 1997)
6	Ecological modernisation	To understand the environmental and social aspects of supply chains by using big data analytics, to gain insight into addressing social or environmental issues (Hazen et al., 2016)
7	Game theory	Using mathematical methods for predicting and explaining competitive phenomena, developing new games (new B2C network) (Camerer, 2011)

8	Institutional theory	Investigating the impact of big data on performance measures such as social, financial and environmental, and to study the data science and big data and their intersections (Hazen et al., 2016)
9	Knowledge-based view and intangible assets	Knowledge required for handling big data, knowledge creation, big data analysis, big data as a source of knowledge, considering big data as an important intangible resource (Hazen et al., 2014)
10	Knowledge management theory	Big data knowledge processes, focusing on the organisational design elements to facilitate levering big data to create value and studying the knowledge sharing processes (Du et al., 2016)
11	Organisational information processing view	Focusing on the information processing mechanisms where big data analytics are deemed as an important information processing mechanism and ultimately focusing on reducing context-specific uncertainty and equivocality (Hazen et al., 2014)
12	Resource dependence theory	The focus is mainly on the supply chain networks, the impacts of the application of big data on organisational power and the relationship with upstream and

		downstream elements (Hazen et al., 2016)
13	Resource-based view	Focusing on big data as an important source that could lead to better performance and innovation, as well as the impacts on the supply chain (Gunasekaran et al., 2017)
14	Social capital theory	Focusing on the interactions between members of the network and sharing data and information (Bourdiew, 1985)
15	Social exchange theory	Focusing on interest-based relationships o social actors, for example, managers' motivations in adopting big data initiatives (Chang et al., 2015)
16	Sociomaterialism theory	Focusing on both social and materialistic aspects of big data analytics capabilities at the same time that is entangled (Kim et al., 2012)
17	Stakeholder theory	Focusing on the impacts of organisational activities (by using big data capabilities) and decisions on stakeholders, trying to satisfy the expectations of stakeholders (Wilburn and Wilburn, 2016)
18	Technology acceptance model	Investigating the factors influencing and determining big data applications, such as ease of use and perceptions towards big data application (Liu et al., 2015)

19	Transaction cost theory	Focusing on minimising the transaction costs by taking advantage of big data analytics technology and maximising the transaction performance (Akter and Wamba, 2016)

However, most of the aforementioned theories are not commonly used in the study of big data. According to the bibliometric literature review conducted by Rialti et al. (2019), dynamic capabilities is the main theoretical approach that scholars have used to investigate the effects of big data on organisations. This is because, in increasingly dynamic environments, organisations will stay ahead can sense opportunities, seize them more effectively, and support the organisational transformation by redesigning and external shaping, and this would be enabled by dynamic capabilities (Day and Schoemaker, 2016; Felin and Powell, 2016; Dixon et al., 2014; Teece et al., 1997).

The resource-based view and knowledge management view are also other popular approaches to studying big data. However, taking the RBV approach will only focus on creating value from new information coming from large data sets and would neglect the vital role of routines in this context; on the other hand, taking the KBV approach will merely focus on knowledge flows coming from big data for decision-making processes as would neglect its significant role as an important source in solving various problems (Rialti et al., 2019). Conversely, taking the DC approach would tackle the mentioned issues simultaneously. Therefore, according to the literature reviews and the discussions in the previous section about dynamic capabilities and their implications in investigating the role of big data on organisational design and decision-making processes, this study aims to use the dynamic capabilities approach as a theoretical lens.

2.7. Developing capabilities

Having discussed the dynamic capabilities in the previous section, this section aims to shed light on some of the important capabilities and factors that influence reaping value from big data. Organisations have realised the importance of developing capabilities to take advantage of big data; therefore, they have spent significant effort in developing those capabilities (Ghasemaghaei, 2021).

“In case an organization is capable of implementing proper systems and developing the right capabilities, the true potential of big data availability may then emerge” (Rialti et al., 2019:2). Accordingly, by developing those capabilities, organisations might be able to scan the environment more effectively to address the dynamism and be more ambidextrous. Additionally, Ferraris et al. (2018) argue that creating value from big data not only depends upon the quality of data but also on the ability of firms to align existing organisational capabilities, processes and culture. Organisational capabilities need time to emerge and one of the main ways to do so is through learning processes (Curado, 2006) which will be discussed in the following sections.

In this regard, specifying the antecedents of DCs would be of great help in terms of developing theoretical propositions. According to the most recent meta-analysis conducted by Bitencourt et al. (2019), the antecedents of DCs are as follows:

- **Resources**: resources would include both tangible and intangible resources such as people, properties, intellectual properties, technological resources and even marketing resources. This is because resources play an important role in making changes. It is important to note that resources can be duplicated across firms, and in order to get a competitive advantage, companies are to reconfigure existing resources. As DCs are defined as the ability of firms to build, integrate and reconfigure internal and external competencies (Zollo and Winter, 2002), it is important to identify how firms are doing so to address big data environments. “Overall, dynamic capabilities are best conceptualized as tools that manipulate resource configurations” (Eisenhardt and Martin, 2000:21). As mentioned earlier, big data is deemed as one of the main intangible resources for organisations.
- **Knowledge management and learning**: Due to the increasing importance of knowledge, the concept of knowledge management has become more prevalent. This is because the availability of IT tools and the increasing number of people who are knowledgeable about the organisation's operations have

made it easier to manage and store information. The concept of a knowledge-based view is also a development of the firm's resource-based view (Easterby-Smith and Prieto, 2008).

Large businesses have realised that knowledge management is an important part of their company's value. According to studies, intangible assets such as brand recognition and unique business processes are often the factors that influence a firm's stock market value. Despite the challenges of implementing knowledge-based initiatives, they can produce exceptional returns. Although it is difficult to measure their impact, knowledge-based investments can help companies achieve their goals (Laudon and Laudon, 2020). Knowledge management and organisational learning are discussed in the following section.

- **Alliance development**: this strategy can be used to gain new knowledge by partnership and it is capable of complementing current resources and capabilities (Bitencourt et al., 2019).
- **Entrepreneurial orientation**: pioneering the discovery of new markets and taking advantage of those markets might require developing new products and services, so taking the entrepreneurial orientation would give companies a competitive advantage (Bitencourt et al., 2019).
- **Environmental dynamism**: this construct is one of the important antecedents of DCs as it would influence the response to changes by pushing organisations to invest more in capabilities to address the new situation and understand the new sources of competitiveness. In other words, the faster the changes, the more reliance on DCs is required (Bitencourt et al., 2019).

2.7.1. Knowledge management and learning

Knowledge is one of the key sources of firms and there has been a swift shift towards learning about the process, people and behaviour from merely producing things over the last 30 years (Thomas H Davenport and Prusak, 1998).

> "Knowledge is a fluid mix of framed experience, values, contextual information, and expert insight that provides a framework for evaluating and incorporating new experiences and information. It originates and is applied in the minds of knowers. In organizations, it often becomes embedded not only in documents or repositories but also in organizational routines, processes, practices, and norms." (Thomas H Davenport and Prusak, 1998:4).

Key assumptions in knowledge management literature include knowledge becoming a critical asset because of the huge amount of social and economic transformations, the changed nature of the work and the increasing importance of intellectual work, and practical knowledge management can be a source of competitive advantage (Hislop et al., 2018).

Knowledge includes both tacit and explicit knowledge in which first is defined as "knowing more than we can tell" (Teece, 2001:13) and the latter includes codified knowledge in different forms. Compared to explicit knowledge which is easily transferrable, representing different ideas, tacit knowledge can be interpreted in various ways and is not easily transferrable (Harlow, 2018). "These differences create challenges for AI and Big Data applications, as AI/Big Data systems attempt to render intelligence and wisdom about tacit and codified explicit knowledge" (Harlow, 2018:402). Knowledge management is influenced by various factors of which Curado (2006) refers to the most significant ones as follows: organisational culture, leadership, organisational interest towards learning, knowledge management processes, organisational structure and technological infrastructure. Some of those mentioned methods directly influence knowledge management like ICT and some might have an indirect influence on KM by means of management of organisational structure or social processes (Hislop et al., 2018).

One critical concept in developing dynamic capabilities is the manipulation of knowledge resources (Eisenhardt and Martin, 2000). Accordingly, an empirical study by Ferraris et al. (2018) revealed that to reap value from big data, a certain amount of knowledge management and big data analytics capabilities are required. Eisenhardt and Martin (2000) also consider DCs as processes embedded in organisations and discuss the role of knowledge management and learning. They argue in moderately dynamic environments, DCs are detailed and analytic processes relying heavily on existing knowledge, whereas in highly dynamic environments, they are unstable processes and experiential depending on the quick creation of new knowledge. In this regard, as DCs are path-dependent, learning mechanisms would guide their evolution (Eisenhardt and Martin, 2000).

There are two kinds of activities that firms might focus their attention on regarding knowledge management strategies. The first is exploration referring to pursuing new knowledge and the second is exploitation which is associated with using and developing extant knowledge (Curado, 2006). Again, in high-velocity markets dynamic capabilities rely less on existing knowledge as they might even be a disadvantage if decision-makers over-generalise from past knowledge. Therefore, these situations require and rely on rapidly creating knowledge specific to the situation (Eisenhardt and Martin, 2000). One example can be rapid learning and creating situation-specific knowledge by means of prototyping and early testing. However, Curado (2006) argues the combination of both exploration and exploitation are not conflicting and would result in synergy and reinforce each other's effects, although it is difficult to implement.

Thus far, knowledge management and learning mechanisms are two important factors in developing dynamic capabilities. In this regard, Mohamud and Sarpong (2016) argue that learning can be considered as an origin and the key ingredient of dynamic capabilities which requires a continuous update. According, companies with the ability to manage various types of knowledge by means of integrating extant and new knowledge, might be able to leverage the organisational capabilities (such as big data capabilities) more effectively (Ferraris et al., 2018). Figure 2-5 shows the boundaries and overlap between dynamic capabilities and knowledge management. As shown, learning underpins knowledge management and dynamic capabilities, knowledge infrastructures would contribute to enabling dynamic capabilities and exploration and exploitation are at the heart of the overlap. Both fields agree that the development of new knowledge is related to the learning process. It seems that the goal of organisational learning is to unify the various insights that are generated by both knowledge management and dynamic capabilities.

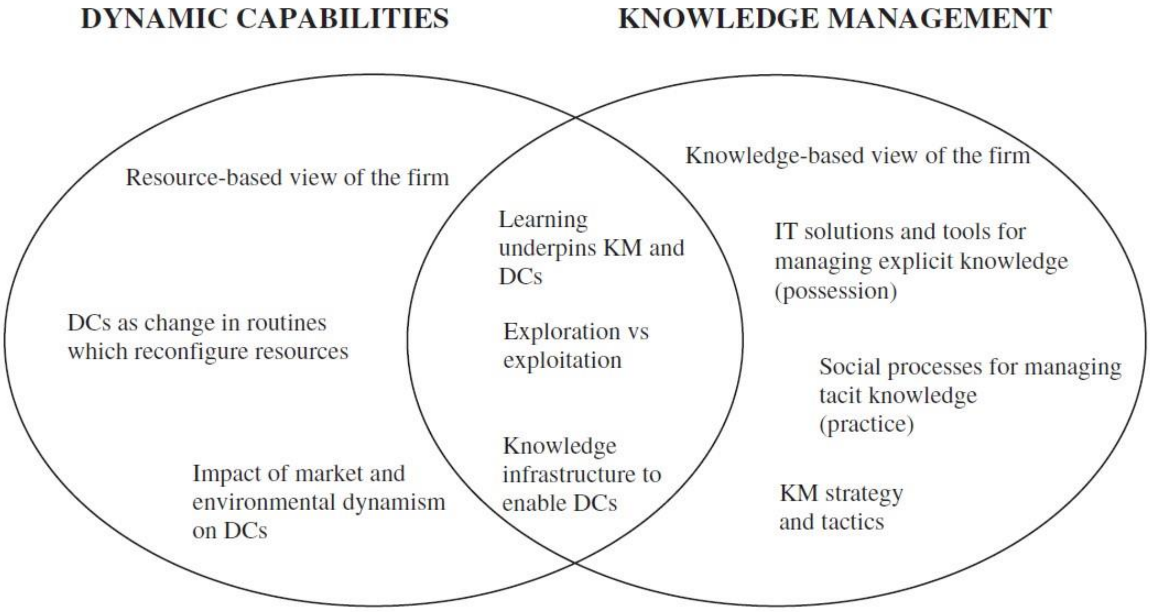

Figure 2-5: Overlap of DCs and KM, adapted from (Easterby-Smith and Prieto, 2008:240)

Like humans, organisations use various learning tools to create and collect knowledge. These tools can be used to improve their efficiency and effectiveness by analysing data, conducting experiments, and receiving feedback from their customers (Laudon and Laudon, 2020). Learning is a process that enables organisations to adapt to their environment by developing new business processes and changing their management decisions. This process is referred to as organisational learning. Organisations that can quickly respond to their environments are more likely to survive than those with weak learning mechanisms (Laudon and Laudon, 2020).

“organisational learning is the acquisition of new knowledge by actors who are able and willing to apply that knowledge in making decisions or influencing others in the organization” (Miller, 1996:486). In other words, the concept of organisational learning states that analysing and disseminating data is the basis for improving the stock of knowledge in an organisation. It can also help improve the performance of an organisation. According to the theory of organisational learning, the multiple factors contributing to knowledge development include acquiring information, interpreting data, and the organisation's memory (Zhu et al., 2021).

Learning is achieved through various mechanisms within and outside organisations, such as training, collaborations, and social media (Doloriert et al., 2017). For example, Doloriert et al. (2017) refer to “personally accredited” learning which is a sort of professional learning and can be transferred beyond the person’s organisation. Curado (2006) argues that the learning process is not only individual but also a social phenomenon meaning that learning is achieved by interactions among people and coordination. Therefore, learning is a dynamic process requiring time to happen and would happen at different levels of individual, group and organisation. According to Crudo (2006) Knowledge acquisition mechanisms could be divided into two groups including internal and external, of which the former refers to learning of individuals inside the organisation by performing various tasks, whereas the latter is associated with acquiring tacit knowledge from outside of organisations such as training.

Eisenhardt and Martin (2000) also argue learning mechanisms lead to the evolution of DCs, for example, repeated practice. In this regard, even small losses would contribute to effective learning as discussed. There are three key mechanisms of learning mentioned by Zollo and Winter (2002) as follows:

Organisational routines and experience accumulation: These routines would either involve the processes for current revenue by using existing knowledge and seeking changes in the existing operations for the future which constitute dynamic capabilities. It is argued that learning processes have to be updated repeatedly in unpredictable and fast-changing environments (Zollo and Winter, 2002).

Knowledge articulation: knowledge socialisation can be considered as one of the organisational learning processes which is associated with individuals sharing their tacit knowledge (Curado, 2006). Collective learning would not happen without members expressing their opinions, and involving in constructive confrontations and challenging others’ views. This would contribute to collective competence by means of knowledge articulation in collective discussions. This higher level of cognitive effort and deliberation can reduce ambiguity by means of increasing the members’ awareness and understanding of existing routines and required changes (Zollo and Winter, 2002).

Knowledge codification: knowledge codification is an even higher level of knowledge articulation consisting of codifying the articulated knowledge into writing forms, for example, in process-specific tools (Zollo and Winter, 2002; Curado, 2006). The literature has accentuated that codification would facilitate knowledge diffusion, and it is a significant element in the capability-building picture (Zollo and Winter, 2002; Curado, 2006). Additionally, tacit knowledge and codified knowledge are considered as drivers of dynamic capabilities (Hidalgo-Peñate et al., 2019).

According to Zollo and Winter (2002:345), some examples of these learning mechanisms might include the "creation of a specific function or department responsible for the process to be learned", and "hiring of 'specialists' in the execution of the task under scrutiny (e.g., creating an M&A team, hiring a TQM expert, defining the function of the chief knowledge officer)". However, these activities would require time, effort, costs, and resources to implement.

In this regard, they also argue that managers who are open to change practices and their organisations are culturally supportive of those mechanisms would be more likely to obtain returns from learning investments (Zollo and Winter, 2002). Organisations that are more divisionised and diversified and also are culturally in support of change would benefit from deliberate learning investments. "The task of the organizational designer, both in concept and practice, is to design structures that put individuals in contact with their relevant environments and to design processes that facilitate learning, sharing and aggregation of knowledge so that the collective organisation can make well-informed decisions" (Felin and Powell, 2016:81).

2.7.2. Leadership

Leadership is also one of the influential factors in a tendency toward information analysis and DC development which is achieved by means of interactions among individuals, processes and structures (Shamim et al., 2018). For example, leaders can actively create an environment where mistakes are tolerated and thereby facilitate trial-and-error learning (the idea of the probe and learn) (Day and Schoemaker, 2016). Accordingly, having access to a deluge of data is not adequate and requires leadership with clear goals and a vision toward big data to make the most of it (Shamim et al., 2018). Even leadership styles could influence knowledge management activities within organisations. For example, KM activities could be enhanced when knowledge managers adopt transformational and transactional styles (Analoui et al., 2013).

A literature review conducted by Kushwaha et al. (2021) using text mining techniques about the "Applications of big data in emerging management disciplines" shows that one of the main factors that emerged from the research is the distrust or trust that businesses have in the overall value of their BDA outputs. This is because many operations-line managers are motivated to build and implement BDA capabilities, but executive-level business heads are more likely to feel that they have a better chance of making more intuitive decisions. This emphasises the significant role of business leaders in coordinating the organisational activities, creating trust among organisational members and eventually making more informed decisions. However, leaders might take different approaches such as authoritative, collaborative or competitive when facing problems (Morais et al., 2020). For example, they might take a more collaborative or disruptive leadership style when facing wicked (e.g.reputation damage) problems (Morais et al., 2020).

2.7.3. Talent management

Another important factor influencing the way organisations reap value from BD is talent management. This is because as data are getting cheaper, data analysts are becoming more valuable (Shamim et al., 2018). This stresses the role of HR capabilities in the recruitment of effective organisational members. According to Mishra et al. (2018), HR would contribute to competitive advantages by understanding the level of knowledge and skills of employees and also attracting more skilled experts or training current ones. This is because some of the tacit knowledge has accumulated in the employees' minds and on the other hand, less qualified members can be a barrier to innovation (Mishra et al., 2018).

2.7.4. Organisational culture

"So organisational culture is the taken-for-granted assumptions and behaviours of an organisation's members. This culture helps make sense of people's organisational context and therefore contributes to how they respond to issues they face." (G. Johnson, 2019:2013).

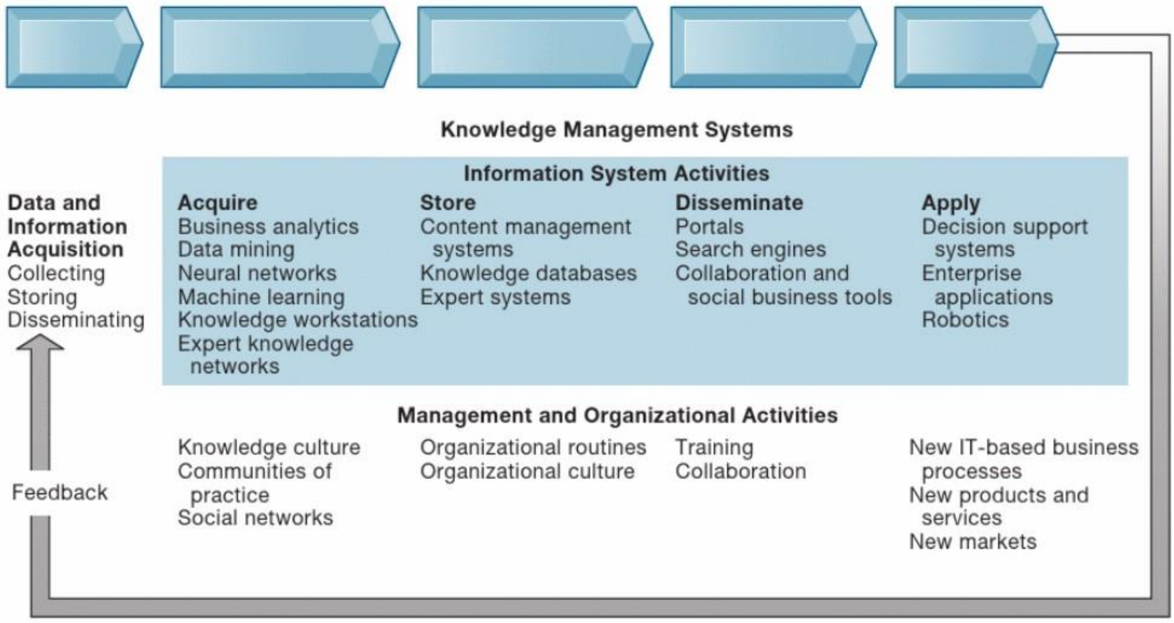

Figure 2-6: KM value chain, adapted from (Laudon and Laudon, 2020:465)

In this figure, Laudon and Laudon (2022) argue that information management is not merely a technical matter, however, it involves management and organisational activities such as training, collaboration, organisational culture, and routines and processes. Therefore, technical information management, including acquisition, storage, dissemination, and application of information, wouldn't be effective as such without organisational cultural support.

Accordingly, One of the most critical factors that organisations need to consider when it comes to making decisions is their culture. This is because changing the way they make decisions could affect the roles and responsibilities of their employees (Frisk and Bannister, 2017).

According to various industry surveys and articles, the culture of an organisation is one of the biggest impediments to the success of implementing BDA (Zhu et al., 2021). The culture of an efficient organisation is also related to its performance. This suggests that the support and culture of the business firms are very important in order to maintain their efficiency. A well-synchronised culture helps enhance the sense of belonging and sustainability of the organisation (Upadhyay and Kumar, 2020).

Thirathon et al. (2017) consider an analytical culture (organisational members' attitude towards the usefulness of analytics) as a competitive resource, which would help them to make the most of big data. This would influence the organisational design by means of supporting advanced analytics and facilitating data sharing because decision-makers in evidence-based cultures tend to rely on data for their decisions (Thirathon et al., 2017). In addition, decision-makers and other organisational members may resist the changes that big data analytics systems might bring about in terms of complementing human intervention in decision-making. Therefore, organisational members who are involved in the processes of data analytics should have at least a partial understanding of big data analytics and related processes and infrastructures (Rialti et al., 2019).

“Mark Fields, President of Ford Motor Company in 2006, famously argued that ‘culture eats strategy for breakfast’, by which he emphasised the importance of culture in defining the strategy of the business. The importance of culture does not mean that strategy is irrelevant, of course: culture should be seen as part of the strategy, something that can be a source of competitive advantage and, to some degree, something that can be managed too.”(G. Johnson, 2019:215). This highlights the importance of culture within organisations as part of the strategy which drives the organisational activities. Additionally, according to the above-mentioned discussions, culture plays a significant role in the effectiveness of information management activities. Therefore, developing an analytical culture and supporting this by executive leaders would contribute to more effective decision-making activities in addressing the big data environment.

2.7.5. Design and structure

The internal design of the organisations is one of the influential factors in facilitating information flow, which is a key part of decision-making processes (Lewis and Fandt, 1989). In this regard, designs such as organic ones with less formalisation and centralisation would contribute to better learning processes and the exploration of new knowledge (Curado, 2006). Additionally, a delegation of decision authorities would facilitate the exploitation of new knowledge (Foss et al., 2013).

Day and Schoemaker (2016) argue understanding the full potential of opportunities that have been sensed and seized by dynamic capabilities might require the effective execution of new strategies. This implementation of strategies in turn, might require a change in the internal design of the organisation which is a third component of dynamic capabilities suggested by Teece et al. (1997). Additionally, building a capacity to sense, shape and seize market opportunities is key to success in fast-changing environments where organisational design plays a critical role in releasing individuals' and teams' creative power and converting distributed information into collective intellect (Felin and Powell, 2016).

2.8. Theoretical model emerged from the literature

The effectiveness of BA is contingent upon other organisational capabilities and resources and their integration (Devece et al., 2017). The current literature is still lacking in the analysis of the ability of organisations to make decisions based on such large amounts of data (big data) (Van Knippenberg et al., 2015). Additionally, based on the review, there is little research on the application of data to date that has helped to provide an understanding of how dynamic decision-making could be improved in such data-intensive environments and the capabilities and processes involved in such activities (Sharma et al., 2010). The second part refers to various approaches to decision-making, of which the rational model seems to be more appropriate in evidence-based decision-making processes. The normative decision-making model mainly relies on evidence and therefore, its outcomes are predictable. This is mainly because the series of actions taken are based on the evaluation of the data which is relevant to the matter under investigation. (Dane and Pratt, 2007). However, the decision-making process is not always straightforward as the eternal environment is becoming more complex and so do decisions therefore, various sources of information might be needed to process immediately (Burstein and Holsapple, 2008). Therefore, decision-makers might face a lack of information, information overload, and outdated information and consequently, they may resort to opinions in the absence of facts, making their decisions vulnerable to various biases. Fact-based decisions are believed to be better in dynamic environments where information is complex and contradictory (Bartlett, 2013). Accordingly, dynamic decision-making processes need to be studied in data-intensive environments to identify how decision-makers change their dynamic decision processes and the influential drivers of those changes to design a more effective organisation. In doing so, dynamic capabilities could be effective. keeping aligned the resources and activities of an organisation along with a dynamic environment is a key theme of dynamic capabilities (Salvato and Vassolo, 2018). The dynamic capabilities approach mainly focuses on organisational and managerial capacity in sensing and seizing opportunities by means of integrating, adapting and reconfiguring activities and core assets (Helfat, 2007; Teece et al., 1999). Accordingly, influential factors in developing capabilities to make sense of big data to improve dynamic decision-making have also been discussed such as organisational learning, knowledge management, leadership, organisational culture, and human resource. Having discussed the main aspects of DCs, this study aims to apply the holistic and multi-level approach suggested by Salvato and Vassolo (2018), considering the corporate level, managerial level, and interpersonal role at the same time. Figure 2-7 shows the theoretical model that emerged from the literature. According to the figure, dynamism is located at three different levels including, Macro, Meso and Micro levels. A holistic approach needs to be taken in order to improve dynamic decision-making in big data environments considering all three levels. In addition, organisational design and culture play crucial roles in doing so. As shown in the figure, knowledge management and organisational learning are also at the heart of developing capabilities to enhance dynamic decision making.

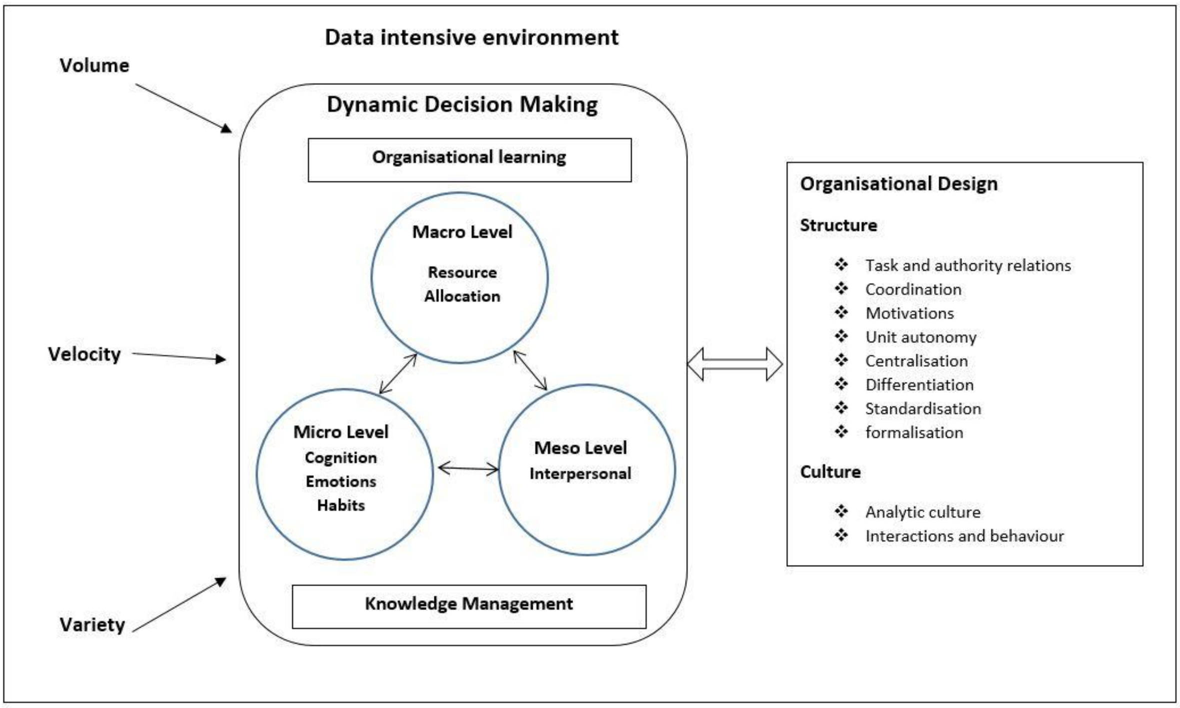

Figure 2-7: Theoretical model emerged from literature (source: author)

2.9. Chapter summary

In this section, the main areas of the literature related to the topic of the study were discussed, including business analytics and big data, decision-making, and dynamic capabilities. In general, the first part emphasises the importance of business analytics in supporting decision-making in organisations to take advantage of opportunities provided by big data. Various decision-making styles were then reviewed. This was followed by reviewing the dynamic capabilities approach as one of the key approaches in coping with dynamic environments. In doing so, various concepts in relation to dynamic capabilities such as organisational learning, and knowledge management were reviewed. Finally, organisational design and structure and their important elements in light of the research question were reviewed. The literature review ultimately resulted in the theoretical model shown in Figure 2-7. The following chapter is dedicated to research methodology.

3. Chapter Three: Research Methodology

3.1. Introduction

In this chapter, the main methodological decisions have been presented to conduct this study, and in doing so, it provides insights into the rationales behind them. This chapter aims to explain the various assumptions and the boundaries of the study's methodological approach. The goal of this chapter is to discuss the various data analysis and data gathering methods used in the study and the rationale for them. They are then used to find meaningful answers to the study's research questions.

Therefore, this chapter delineates the overall research framework and the underlying research philosophy and approach. It also explains the research design, data collection methods and techniques followed by contextual information around the business environment in which chosen cases operate.

According to Leavy (2014:2), research can be separated into three main components. First is the research philosophy entailing paradigm, ontology and epistemology. The second is praxis, which concerns methodology, theory, techniques and genre. And the third one is associated with research ethics and values. In this regard, research practice is guided and led by philosophy and the relationship between the two is bridged by ethics. Accordingly, a set of philosophical assumptions, data collection methods and techniques, an approach toward the data analysis, and a written record of findings are the main components of a good qualitative research design (Myers, 2019). Hence, this chapter aims to discuss the components mentioned above in the study.

The research follows the constructivist approach ontologically and the interpretive approach epistemologically, focusing on the meanings in the context to extract them by investigating rich and illuminating data. The studying of such data that includes narratives, thoughts and interpretations of participants who participate in social processes would contribute to providing a detailed description and understanding of the impact of big data on organisational decision-making processes and structure.

The research methods are designed to collect rich and illuminating qualitative data from various cases by means of interviews. The study includes 9 cases from across the United Kingdom.

3.2. Revisiting the research question, objectives, and scope of the research

This study aims to investigate how big data influences decision-making processes and, consequently, organisational design. It aims to investigate how organisations make sense of big data by changing their decision-making processes and developing new capabilities. This is because business environments are getting increasingly dynamic and complex due to the radical advances in data science, information and communication technologies (particularly big data) (Grable and Lyons, 2018), bringing about opportunities and challenges (Müller et al., 2018).

The sheer amount of data available to organisations has made decision-making processes challenging as such data sets are too complex and voluminous to be able to be processed by traditional tools and techniques (Thomas H. Davenport et al., 2012). Investigating the influence of such data sets on organisations calls for focusing on a few specific areas such as knowledge management, capabilities necessary to deal with big data, organisational routines and processes, and data itself as a source (Rialti et al., 2019). Even more, decision-makers have a limited information processing capacity, and organisational structure could be considered an optimal response to it (Kennedy, 1994). Therefore, to keep pace with the fast-changing environment, decision-makers need to change their decision-making processes. Addressing the questions, including how organisations make those changes, what are the key drivers of those changes, and what are the necessary capabilities in doing so, will have important implications for organisations with regard to coping with such data-intensive environments.

Specifically, the research question will be how big data influence decision-making and consequently organisational design. The objectives of this research include:

- To identify the ways in which decision-makers in data-intensive environments are changing their decision-making processes.
- To identify the factors which decision-makers consider most influential in driving those changes.
- To identify how those changes influence organisational design to enhance dynamic decision-making.

- To develop a framework to enable decision-makers to assess and improve their strategies for adapting to data-intensive environments, including the required capabilities.

3.3. Theoretical basis for the research

The choice of the research philosophy, methods and techniques is established based on the premise that individuals, their interactions and participations in the social world would lead to a specific meaning and status, and these continuous interactions would contribute to understanding the social reality (Orlikowski and Baroudi, 1991). It seems the “multifaceted” nature of decision-making calls for a deep analysis of the phenomenon within a specific context and on particular participants (Teale, 2003). This would be achieved through analysis of participants' narratives, beliefs and interpretations. The following section elaborates on the rationale behind the conceptual model of the study and the central role of the miso-level (see section 2.8).

This study uses a multi-level view of DC as a lens. This is because, On the macro level, Eisenhardt and Martin (2000) conceptualise DCs as decision-making rules and algorithms, while Teece (2007) refers to organisational routines. In this sense, Salvato and Vassolo (2018) argue that considering DCs as repeated routines would make it difficult to locate the sources of dynamism at individual levels. However, on the micro level, DCs could be interpreted as decision-making activities based on the skills of top executives (Adner and Helfat, 2003; Teece, 2007). Considering DCs as micro level, which focuses only on top managers, would limit the role of lower-level employees and obscure the ways of generating systematic processes (Salvato and Vassolo, 2018). Therefore, to take a holistic view and address the contrasting views of DC, this study aims to apply the multi-level (integrated) DC approach suggested by Salvato and Vassolo (2018), in which persons and interpersonal interactions have been given a central role.

The impact of big data is studied on dynamic decision-making processes to identify how organisations change and design both those processes and their organisational structure to better make sense of big data. To do so, as discussed earlier, DC would facilitate those processes. Hence, the DC lens is considered to define coding labels at micro, macro and meso levels during the analysis process.

One of the important aspects of every study is to consider its contribution to knowledge. In this regard, the development of concepts, generation of theory, drawing of specific implications, and contribution of rich insight are four types of generalisations mentioned by (Walsham, 1995). This research aims to provide both theoretical and practical contributions. For theoretical contribution, contribution to decision-making theory by providing insights about dynamic decision-making in the context of big data and a better understanding of organisational strategies for working with and leveraging value from big data. This is because, as mentioned earlier, there is little study on the non-technical aspects of big data and how it affects decision-making processes. As mentioned earlier, effective organisational structure can be a response to limited information processing capacity. In this regard, identifying the ways in which decision-makers change their decision-making processes in data-intensive environments would be helpful in providing a detailed description and understanding of the impact of big data on organisational design and structure. In doing so, identifying the most influential factors would be helpful in developing a framework that would guide decision-makers to enhance their decision-making strategies and facilitate leveraging big data by designing a more effective organisation. It is important to note that the change process is ongoing and, therefore, based on the dynamic environment, it will also change to cope with environmental dynamism. In this study, organisational change is considered as a dependent variable, however this study acknowledges that the designed structure would affect decision processes in return. Hence, the researcher aims to study the impact of organisational structure as a dynamic capability on decision-making processes in future studies. In addition, for the practical aspect, it contributes to guiding practitioners in evaluating their organisations to inform improvement to become better enabled for big data-driven decision-making.

3.4. Research philosophy and approach

The study's main objective is to expand our understanding and knowledge about big data's role in organisations' design. This discipline is in its infancy and has a limited amount of knowledge. One of the most effective ways to expand our knowledge about the various facets of big data is by conducting a study on how organisations can improve their operations by implementing effective strategies and techniques related to big data. This study is an exploratory one, which means it takes a detailed and qualitative approach to its main research question.

Philosophy underlines the form of research by discussing the nature of the phenomenon being investigated, referring to ontology and the ways of understanding it, which refers to epistemology (Van De Ven and Proquest, 2007). Ontology comes from the Greek words meaning “thing” or “rational account”. In classical philosophy, ontology is associated with the science of being, attempting to supply reasoned and deductive accounts of the things that existed (Given, 2008). Epistemology stems from the Greek words “*episteme”* (knowledge) and “*logos”* (explanation) and is one of the key areas of philosophy. It is mainly involved with nature, sources and limits of knowledge, attempting to address the key question, “what constitutes knowledge?” (Given, 2008; Mathison, 2005). This is important because the meanings being attributed to constructs, the relationships between them and theoretical statements heavily rely on philosophy (Van De Ven and Proquest, 2007).

The first layer in the development of knowledge is specifying the philosophical stance of the researcher. These underpinning assumptions play an important role in framing the research question, methodology and interpretation of results (Saunders et al., 2009). Establishing a philosophical position might be influenced by some factors, including practical considerations (time and financial position) and accessibility to data (Hathaway, 1995). In a reflexive process of philosophical positioning, there is an interconnected relationship between research design, research philosophies, and the beliefs and assumptions of researchers. It is important to note that there are different philosophical positions in business and management because its theoretical base is drawn upon various disciplines such as social, natural, applied sciences and humanities. Hence, philosophical disagreements are inevitable and inherent parts of the study (Saunders et al., 2009).

3.5. Philosophical perspective

In the previous section, the importance of research philosophy was discussed. In this section, the main philosophical positions in sciences and the researcher's approach to them are explained.

Some might critique the objectivity and rationality of the social sciences on the ground that they are intensely subject to ideologies, social norms, culture and language, and mental biases that form their process and inputs of them (Van De Ven and Proquest, 2007). On the other hand, relativists and social constructivists attribute science to the sociological paradigms the scientific community agrees upon, and there is a consensus (Van De Ven and Proquest, 2007). Below is a brief comparison between positivist and interpretive approaches, helping to understand the philosophical stance of the study.

A positivist study is a type of research that aims to improve the understanding of a phenomenon by testing theories (1991; Eisenhardt, 1989). In terms of decisions and actions, most positivist researchers are associated with a rational or at least boundedly rational approach. The above-mentioned was about the ontology of the positivist approach. In terms of social reality, "[t]he assumption about social reality is that humans interact in relatively stable and orderly ways and that conflict and contradiction are not endemic to organizations and society." (Orlikowski and Baroudi, 1991:10).

Positivist researchers tend to take a deductive approach (epistemology) to understand the unilateral or causal relationships between various concepts. In other words, the researchers test the hypotheses developed from theories by verifying and falsifying them. In this regard, three terms could be considered, including explanation, prediction and control. If particular principles and their impact on the occurrence of events are known, then they could be used to predict and control the events (Orlikowski and Baroudi, 1991). For example, experiments and sample surveys are among the positivist methodologies that could be controlled. As another example, inferential statistics (as a decent analysis method) are used to predict the outcome of events. Although positivist research methods are really useful for testing theories, they tend to ignore the historical context of the events. Furthermore, it could be argued that those methods resort to a more deterministic approach in explaining phenomena (Orlikowski and Baroudi, 1991). According to the nature of the research question and aims and objectives, the phenomenon is investigated in its natural context; therefore positivist approach may not be suitable for this study.

Assumptions made by positivist and interpretive approaches tend to vary as well. The interpretive approach considers social actors as an important factor in understanding reality, whereas this is not the case for positivist approaches. Reality is made of subjective experiences and social processes that are not inflexible and cannot be understood independently. “[T]he aim of all interpretive research is to understand how members of a social group, through their participation in social processes, enact their particular realities and endow them with meaning, and to show how these meanings, beliefs and intentions of the members help to constitute their social action.” (Orlikowski and Baroudi, 1991:13). According to Klein and Myers (1999), there is a reciprocal relationship between context and phenomenon therefore, context is of high importance in interpretive studies. This is why it is important to understand the meanings people attribute to phenomena and how complex they are, and how people make sense of the situation. Similarly, the context (data intensive environment) and how people make sense of their decisions within it is key in this study.

Positivist approaches tend to study the organisational structure and social relations more objectively and tend to ignore the subjective meanings which are important from the ontological perspective in interpretive studies. Social interactions and individuals’ roles lead to certain meanings and statuses (Orlikowski and Baroudi, 1991). These continuous interactions between social actors lead to a better understanding of social reality, which may not be possible to be studied by positivist approaches (Lee, 1991). Therefore, members of the social system play a key role in understanding, measuring and characterising social systems (Orlikowski and Baroudi, 1991).

It seems the concept of the interpretative perspective is a promising approach to studying the world since it does not regard it as a fixed object. Instead, it sees it as an emergent social system that is embedded in people's subjective experiences and consciousness. This would allow the researcher to gain a deeper understanding of the various attributes of reality that are reflected in its emergence.

In general, an epistemological perspective is a set of beliefs and principles that can be used to guide a study. This can be influenced by the study's goals and by the researcher's own ideas about how to approach the project. Once a researcher has established a set of beliefs and principles, he or she can then use these as the basis for conducting a study. The way a researcher chooses to approach the study has a significant influence on the way he or she views technology (big data). This is because those who study it tend to focus on the boundary between social and physical phenomena. Therefore, before they can start conducting a study, they must first establish a clear understanding of the nature of technology in an organisation. This discipline is very important to study as it involves the role technology plays in organisations. The study's main objective is to explore how technology can help improve the design of organisations.

This study takes the interpretive approach based on the arguments mentioned above. The following section elaborates on the reasoning methodology adopted for this research.

3.6. Reasoning methodology

For this study, a mono-qualitative method has been chosen based on the interpretivism philosophical stance of the researcher and also the nature of the research question. The qualitative study tends to be inductive, constructive, and interpretive, but it does not necessarily mean that researchers always subscribe to these options (Bryman and Bell, 2015).

Unlike the deductive approach, dominant in natural sciences and which is concerned with testing theories developed based on the literature, the inductive approach aims to understand the way in which participants interpret their world. In this regard, researchers in favour of induction might criticise the deduction on the ground that it does not provide explanations for what is happening and merely rely upon rigid methodology. In addition, because induction is likely to focus on a specific context, it might be more appropriate in small samples (Saunders et al., 2009). Accordingly, it is important to note that it does not generalise the findings to the population because, unlike deductive methods, sampling is not based on probability sampling. Therefore, researchers following this approach are likely to use qualitative research methods (grounded theory approach, for example) and consequently related data-gathering techniques (semi-structured interviews, for example) to gain deep insight and understanding of the phenomenon under investigation.

Compared to a deduction approach which moves from theory to data (top-down) and induction which moves from data to theory (bottom-up), abduction is concerned with shifting back and forth between data ad theory (Suddaby, 2006; Shannon-Baker, 2016). Existing theories would be helpful in developing new conceptual frameworks. Generally, specifying the reasoning type could help the researcher to design research and choose a more appropriate methodology (Saunders et al., 2009). Based on the arguments in the previous section, the nature of the research question which aims to explore what is happening in the study's context by developing theories, the reasoning methodology leans towards the inductive approach. However, as existing theories would be helpful in developing new concepts, the abductive methodology was adopted for this study. This helped the researcher to stay focused on the research question by constant shift between data and literature, and also establishing the main themes of the study.

3.7. Research methods

3.7.1. Qualitative research method

This section further illustrates the qualitative research method and the rationale behind the chosen method. Based on the fundamental epistemological assumptions of the researchers, a qualitative study could take one of the interpretive, positivist, or critical approaches (Urquhart and Fernandez, 2013). Qualitative studies have gained a lot of attention from scholars because of the features and opportunities they offer. This is evident in the review of management publications over forty years by Üsdiken (Cassell et al., 2017). This method has also got debates and critiques regarding data analysis, the role of software and philosophical approaches (Cassell et al., 2017).

This study seeks to study the decision-making processes (as a particular management activity), and how managers design their organisations by developing dynamic capabilities to keep pace with fast-changing and data-intensive environments. Teale (2003) believes that many of the studies conducted in the field of decision-making have a positivist approach. For example, most of the research in cognitive psychology which has led to general theories in human behaviour, are conducted in laboratories under control. However, studies with inductive reasoning, which are carried out in specific contexts in the real world, have recently been increasing in management studies. In addition, in reality, managers encounter uncertainty and complexity which requires more practical and context-specific studies (Teale, 2003).

If we take an objectivist approach, we assume that decision-making processes in management are similar in all organisations and are generalisable. For the sake of simplicity, there are job descriptions and procedures that managers are required to stick to them. By taking this approach, researchers seek to explore generalisable laws in management behaviour which can be predictable in the future. However, this study attempts to gain a richer understanding of a phenomenon in its organisational context.

Saunders et al. (2009) believe that social interactions are ongoing, and consequently social phenomena are changing and being revised as time goes on. Decision-making processes are also changing. For example, as mentioned before, complexity and uncertainty due to recent development in technologies change decision-making processes. In this regard, McAfee and Brynjolfsson (2012) believe that big data has revolutionised data science and decision-making. They argue that nowadays, decisions that are more based on experience are shifting toward data-driven decisions.

Considering various definitions of decision-making, there are some key terms worth paying attention to including individual and social phenomena (Harrison, 1995), ongoing process (Mintzberg, 1983), evaluation and commitment (Teale, 2003). Accordingly, Teale (2003) considers decision-making as a “multifaceted” phenomenon which might be better analysed in a specific context and on particular participants. In addition, unlike the objectivist approach that seeks to discover universal facts about a specific phenomenon, this study tries to develop concepts about the particular phenomenon in its natural context through narratives and different views of individuals. For example, managers might interpret the situation differently based on their experience, knowledge and the level of complexity they face. In this regard, Teale (2003:105) highlights Pirsig's argument (1991) which says "Objects of scientific study are supposed to hold still. They're supposed to follow the laws of cause and effect in such a way that a given cause will always have a given effect over and over again. Man doesn't do this."

Similarly, Orlikowski and Baroudi (1991:15) refer to another comparison between positivist and interpretive approaches as follows: "in positivist research we are talking to processed people in the sense that they can only answer in terms of our questions and our categories. In contrast, interpretive techniques allow participants to use their own words and images, and to draw on their own concepts and experiences."

According to the literature on decision-making, early works on decision-making had a positivist assumption wherein decision-makers see the world as it is (Martin and Parmar, 2012). For example, rational models could be classified into this group. Dane and Pratt (2007) argue that normative (rational) decision-making relies on data and evidence, and its outcomes are predictable beforehand because a series of actions rely on data analysis and evaluation of information directly related to the issue. In other words, reasonable outcomes are a result of rational decisions. However, non-rational decision-making majorly relies on intuition, perception and understanding of decision-makers which comes from the decision maker's experience and feelings. In the real world, most of the decision-makers incorporate the concepts of those mentioned approaches at the same time rather than following one particular approach (Fulop, 2005). Furthermore, on the strategic level, Eisenhardt and Zbaracki (1992) highlight the limits of strategic decision-making, such as bounded rationality, because individuals (cognitively limited) are decision-makers. Therefore, chance would disturb the decisions. Furthermore, cognitive limitations could be deemed as an effective factor in respect of decision-making because decision-makers have different views of goals. Hence, considering the mentioned affective factors, positivism does not seem to be a suitable approach in this regard. Martin and Parmar (2012) also argue that recent works in "social cognitive sciences" have questioned the early assumptions in decision-making models.

Therefore, according to the philosophical stance of the researcher, the essence of the research question, the reasoning technique and the context in which this study is carried out, the qualitative research method seems to be more suitable. The following sections elaborate on this methodology in detail.

3.8. Research design

3.8.1. Case study

This section aims to provide an overview of the case study that is used as the main research strategy in this study. It also aims to explain how the design of the study is influenced by the case study's choice.

There are various research methods that researchers can choose from, depending on their research design. Those methods can be an experiment in the lab, a survey, case studies, visual anthropology (shooting videos), a study of historical archives, and so on. Each of the mentioned methods follows a different method of data collection, analysis, and even presenting the results. Not only are those methods of various techniques, logic and procedures but also they have their own advantages and disadvantages.

Thus far, the researcher has discussed the research philosophy, chosen methodology and reasoning technique that drives his research design. This section aims to discuss the reasons for choosing the case study method in detail. Yin (2018) argues, that when choosing various modes of inquiry, researchers need to consider three conditions as follows.

The first one is the form of the research question, which is probably the most important part of the research. Some methods are suitable for answering the "how" and "why" questions such as case studies, experiments and study of history. This study particularly focuses on "how" questions aiming to address the question how organisations make sense of big data by developing new capabilities and redesigning their decision-making processes. Hence, makes sense in an exploratory study to examine this in some depth/richness/detail to gain useful insight into these processes.

The second one is about the amount of control over the behavioural events helping further distinguish between the available modes of inquiry. Some studies might look at the historical data such as studying history with not interfering in the events, whereas in action research, for example, interventions might be tested (Payne and Payne, 2004). Case studies would also be suitable methods where there are no interventions and control over the phenomenon being studied (Yin, 2018). However, there might be action research case studies as well. But this is not the case for this study. The third condition is about how contemporary the phenomenon under investigation is. As this study has no intention of changing or interfering with social events, has an exploratory nature answering "how" questions and focuses on a contemporary phenomenon (big data), case studies seem an appropriate and relevant approach to the research. Having discussed the rationale for choosing case studies, the following sections delineate this particular method in detail.

Case study research has been regarded as a valid technique for conducting studies on various aspects of information systems. It can be used by researchers to look into the different aspects of an organisation's information systems (H. K. Klein and Myers, 1999).

The case study is deemed as one of the most frequently used, though contested, methodologies in social sciences (Yazan, 2015). According to Yin (2018), the case study method refers to a deep study of a contemporary phenomenon in a real-world situation which can rely on more than one source of evidence. In other words, Payne and Payne (2004) define it as a rather detailed investigation of a specific social unit helping to develop fresh and in-depth insights. "The case study is a research strategy which focuses on understanding the dynamics present within single settings."(Eisenhardt, 1989:534). Case studies might include several levels of analysis or could be single or multiple cases. In terms of types of data and evidence, both qualitative and quantitative data collection techniques could be employed, such as interviews, observations, documents and surveys. Based on the philosophical underpinnings of the research, case studies could be used to test theories (positivist studies), build theories from data, or provide descriptions (Eisenhardt, 1989).

Kathleen Eisenhardt and Robert K. Yin are probably among two of the most prominent and popular authorities in the case study approach, whose publications date back to the 80s (Cassell et al., 2017). Eisenhardt deems a case study as a "bridge" between rich qualitative data and theory testing (deductive approach), remaining true to the positivist case study approach, whereas Yin refers to inducing theories from exploratory and, developing new insights and theoretical frameworks from explanatory case studies.

However, both agree on the role of multiple case studies in building more robust and testable theories (Cassell et al., 2017).

It is worth noting that there are differences between case studies and laboratory experiments. According to Klein and Myers (1999), context is an important factor in interpretive studies, and so are the reciprocal effects of it and the phenomena being investigated. Case studies highlight the key role of the context within which phenomena are investigated. But this is not the case in laboratory experiments where context is controlled, or the phenomena tend to be separated from their context (Eisenhardt and Graebner, 2007). However, although case studies (theory building) are subjective, an intimate adherence to data might result in a remarkably objective analysis (Eisenhardt and Graebner, 2007)

As mentioned in the previous discussions and based on the nature of the research question, this study investigates a phenomenon in its natural context. The phenomenon that is not separated from its context (data-intensive environment) is a vital aspect of this study. In addition, social actors (decision-makers) play an important role in constructing meanings and creating reality by interpreting the data and changing decision-making processes to make them more sensible. Therefore, a multiple case study approach has been chosen for this research to gain an in-depth understanding of the topic concerned. Compared to a single case study, multiple case study is considered more robust, and the evidence is more compelling (Yin, 2018). In this sense, Figure 3-1 shows the different steps of conducting multiple case study research. The model of the study mentioned in Figure 3-1 is conducted for each case separately. Having studied each case, cross-case conclusions are drawn, resulting in the final framework of the study being shaped.

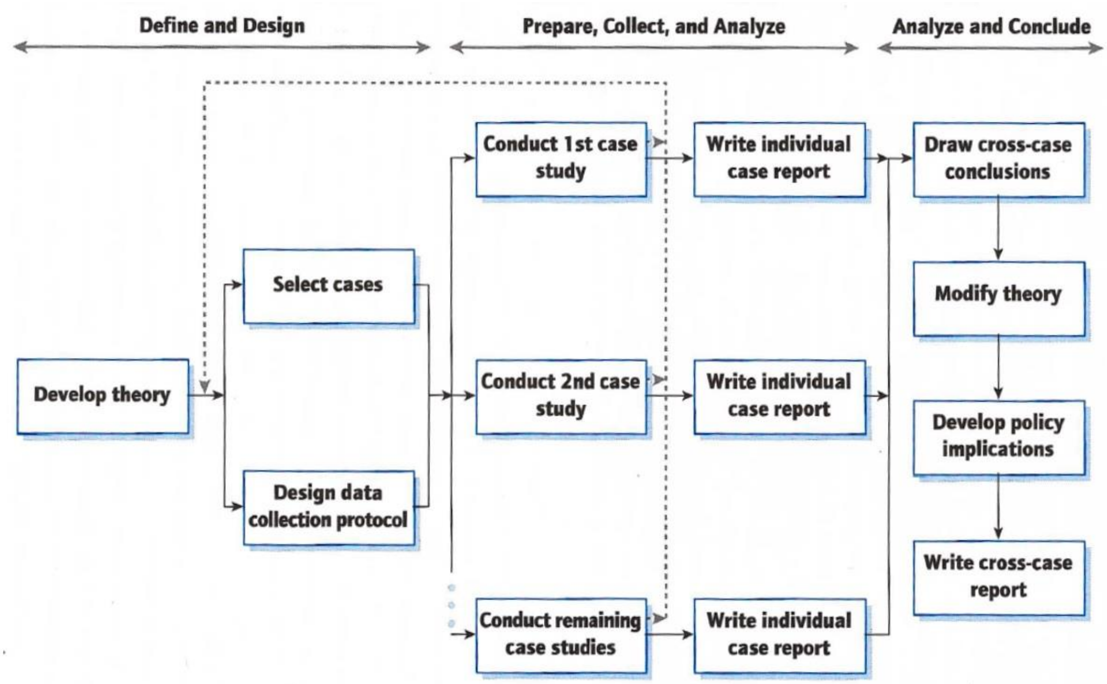

Figure 3-1: Various steps in conducting multiple case studies adapted from Yin (2018)

3.8.2. Validity and reliability

Similar to any other research method, the case study also has its own advantages and disadvantages.

It is important to discuss the Validity, reliability and generalisability of qualitative studies, particularly case studies. This is because research is the outcome of the interaction between the researcher and the events being investigated, and researchers might have various views on interpreting their findings (Lindgreen et al., 2020; Orlikowski and Baroudi, 1991). To address this issue, the validity and reliability of the case study can be assessed through the following tests: construct validity, internal validity, external validity, and reliability (Lindgreen et al., 2020; Yin, 2018).

Construct validity: as discussed earlier, case studies are capable of producing rich and detailed descriptions of the phenomenon being studied. Those descriptions are typically relying on various sources of data to be produced (Yin, 2018; Cassell et al., 2017). According to Yin (2018), construct validity is concerned with creating a set of operational measurements of the concepts under investigation. This might be due to the researcher's preconceived notions of the concepts. He refers to some strategies to improve the construct validity by using multiple sources of evidence (interviews and company information, videos, documents etc.), and to review the draft of case study report by key informants. Therefore the draft of case study were sent to the interviewees to review. The first tactic (triangulation) is relevant because it would encourage the convergent lines of inquiry as case studies to owe their quality and richness to the use of evidence, and this tactic should be considered during the data collection stage (Lindgreen et al., 2020; Yin, 2018).

Internal validity: As discussed earlier in this chapter, case studies can be exploratory, explanatory, or descriptive. Internal validity applies to studies that are seeking for causal relationships (for example, how variable A leads to B), particularly in experimental and quasi-experimental studies, to improve the quality of the investigation (Yin, 2018). There are some tactics to address/enhance internal validity such as pattern matching, rival explanation, and using logic models, however this tactic is inapplicable to this study as it is not seeking causal relationships between variables.

External validity: This test is concerned with the generalisability of the results of the study. Most of the case studies generalise to theory (analytical generalisability) rather than the population (statistical generalisability) because they are not based on statistical sampling and also merely investigate a contemporary phenomenon in its natural context (Yin, 2018). Limitations of case studies are well written (some are already mentioned earlier), however some scholars believe that the results of case studies are likely to be empirically valid.

> “the theory-building process is so intimately tied with evidence that it is very likely that the resultant theory will be consistent with empirical observation … This intimate interaction with actual evidence often produces theory which closely mirrors reality” (Eisenhardt, 1989:547).

Reliability: One of the important features of quality research is that the findings can be repeated. On the ground that case studies are mainly subjective studies, their reliability and replicability of them are questioned (for example, another researcher might recognise different patterns of meaning in the same data set we are looking at) (Rosen, 1991). The aim of this test is to assess the replicability of the study (reducing the error and bias) to make sure if another researcher investigates the same case through the same procedures, he will achieve the same results(Yin, 2018). In this regard, Yin suggest the documentation of the study procedures. This would be achieved via either developing a case study database or a case study protocol, making all the procedures as explicit as possible.

3.9. Using the Grounded Theory Method (GTM) in building theories from cases

Due to the increasing number of studies on the interactions between human agency and socio-technical processes, many of these have been focused on the interrelationship between these two elements. Despite the wide variety of topics and methods that are commonly used in the field of information systems, two major issues have become very important to the discipline. First, it is very important that the researchers understand the interactions between human behaviour and computer-based systems (Orlikowski and Baroudi, 1991). Second, Due to the increasing number of studies on the interactions between computer-based systems and human behaviour, it is very important that researchers develop new theories that can explain how these technologies can interact with people. This is also a reason why it is very important that the members of the IS community work on developing new methods and techniques to improve the understanding of these technologies (Weber, 2003).

An inductive approach is helpful for studying new technological phenomena. It allows researchers to identify the potential influences of new technology without having to go through extensive theoretical knowledge (Sarker et al., 2000). This approach is especially beneficial when the technological changes being studied are so novel that they cannot be easily explained by existing knowledge. It is also argued that the grounded theory approach is useful when the researcher does not have to go through extensive theoretical knowledge. This allows them to create a more accurate and contextual theoretical account of the potential technological changes (Orlikowski, 1993). However, the key argument is that an inductive approach builds theories from data and does not test the existing ones.

The GTM was first introduced by Glaser and Strauss in 1967 with the aim of building theories from empirical data. It is important to note that GTM does not try to prescribe solutions but tries to explore the current situations(Urquhart and Fernandez, 2013). To do so, researchers who adopt GTM constantly compare data and theories till reaching theoretical saturation (Urquhart and Fernandez, 2013; Eisenhardt and Graebner, 2007). Urquhart et al. (2010) believe that GTM is rather effective in context-based and process-oriented studies. Accordingly, as this study is also context-based and tries to explore the current happening within a real context, GTM seems to be a more appropriate method. In addition, GTM provides flexibility in terms of philosophical stances as it takes a neutral view allowing GTM to be used in various methods such as mixed methods (Urquhart et al., 2010).

In order to develop a more accurate and contextual theoretical account of the potential technological changes, it is important that the researcher engages with existing literature. Urquhart and Fernandez (2013) noted that this process helps researchers move away from their "empty head" and start to develop an “open mind”.

There are also two different perspectives on the role of reviewing the literature when it comes to grounded theory studies. One of these is the first perspective, which focuses on the emergence of theoretical categories. According to Glaser, the concept of conceptualising a phenomenon is an iterative process. According to Glaser (Glaser, 1992), the process of grounded theory is an inductive one, which allows researchers to develop theoretical categories as they try to make sense of the data collected during analysis. Plus, he argues that theoretical constructs are only products of data analysis. This means that they cannot be pre-defined. Another perspective which is based on the work of Strauss and Corbin (Strauss, 1990), who presented the grounded theory approach in 1990, argues that existing literature can help create theoretical sensitivity and provide a framework for a study. For instance, researchers can use a coding paradigm to study causal conditions. Glaser argues that this approach prevents the emergence of new ideas by forcing data into pre-defined categories.

3.10. Potential researcher bias

Central to research, and more importantly data collection, are researchers themselves particularly in qualitative studies (Chenail, 2011). This study's ontological position suggests that people's knowledge, views, understandings, interpretations, experiences and interactions are meaningful properties of social reality which This study's research questions are designed to answer. This study's epistemological position suggests that a legitimate way to generate data on those ontological properties is to interact with these people, talk to them, listen to them and gain access to their accounts and articulations. Accordingly, R. B. Johnson (1997) believes that the accuracy of understanding participants' thoughts, opinions and beliefs is of high importance. This is because the bias in qualitative research is inevitable and it might creep into the results not only during the interview (data collection process) but also in reporting stage as well. He highlights some of the strategies which can be used, in mitigating, if not eliminating the possible biases. He deems researchers as "detectives" who should take a neutral position towards the data and evidence, carefully examining the existing evidence. Reflexivity is one the effective ways of reducing the bias in interpreting the field data Which involves self-awareness or "critical self-reflection". In doing so, researchers need to be aware of their own possible biases and Predispositions that might influence the results (R. B. Johnson, 1997). Pattern matching (predicting this series of results), peer review, theory and data triangulation, and participant feedback are also among the factors that can be considered in addressing the potential bias issue in qualitative research (R. B. Johnson, 1997). In this study, researchers tried to approach the field and data without any assumptions about the data and took a more neutral approach to minimise bias. In addition, prior to actual interviews, interview questions were peer-reviewed and mock interviews were conducted to enhance the quality of interviews and minimise biases.

3.11. Research focus

3.11.1. Participant, sample size, and recruitment

Having decided on a case study approach, another important decision is how many cases and case selection criteria. Cases are not selected based on probability sampling methods; they are rather selected based on criteria related to characteristics of similarity in relation to the research problem/phenomenon. In other words, “the goal of theoretical sampling is to choose cases which are likely to replicate or extend the emergent theory” (Eisenhardt, 1989:537). Case sampling is one of the most common challenges in developing theories. This type of study can be argued that it doesn't test the theory, as it doesn't represent a specific population. However, it can be selected according to certain criteria, such as the level of illumination and appropriateness in order to study the relation between various constructs (Eisenhardt and Graebner, 2007).

The cases of this study include organisations that are using large datasets as a main source of information for decision-making based in the UK. Convenient Sampling and snowballing methods were used in selecting cases. Case selection stopped when theoretical saturation was reached. For this study, nine organisations were selected, from which twelve people were interviewed. In this regard, business intelligence and analytics experts, data analysts, data scientists, data officers and managers (from various levels of organisations) who deeply understood organisational and information processing mechanisms were interviewed. The identity of the interviewees was kept anonymous, as agreed with them, by using the letters A to P to represent their names. Every letter represents a person from a company, apart from letters B, C, and D, three people from one company, and letters N and P, two people from a company. Those letters are used in the analysis chapters as references. Company names and identities of interviewees are kept strictly anonymous in all publications.

3.11.2. Ethics

Earlier in this chapter, we discussed research bias which is part of the broader topic called “research ethics”. “Ethics is concerned with the study of morality and the application of reason to elucidate specific rules and principles that determine morally acceptable courses of action. Ethical theories are the codifications of these rules and principles” (Crane et al., 2019:8).

Ethics is one of the moral systems in each society permeating people’s lives, and as societies develop and become more complex, regulations also need to be updated (Eriksson and Kovalainen, 2015); for example, GDPR came into law in May 2018. Ethical principles are part of every research governing all activities from research design to writing up and reporting the results.

Maintaining appropriate ethical standards is considered as one of the vital parts of every study (Peled and Leichtentritt, 2002). As mentioned earlier, interacting with people and communities might cause some ethical issues. Accordingly, Lapan et al. (2012) refer to three principles that can lead researchers to conduct their studies ethically including respect, beneficence and justice. In addition, there might be other factors to be considered such as informed consent, data protection, and confidentiality (Lapan et al., 2012). In this regard, Yin (2018) refers to some of the ethical standards that researchers might strive to those levels while conducting research, including avoiding plagiarism, not falsifying the information, taking responsibility for their own work and being honest.

It is not easy to draw a clear line between right and wrong as people might interpret various situations differently, particularly the complex issues that are becoming more common in business settings. Therefore, following standard ethical frameworks would be helpful in maintaining high ethical standards. In this regard, Institutional ethical approval was sought for this study called “Ethos” by Submitting a project proposal, participant information sheet and consent form. The application was reviewed by the Business and Law Research Ethics and Governance Committee and received a favourable ethical opinion. For example, the names of the organisations under investigation are fully anonymous, and participants' personal information, such as their names are kept anonymous, not to be mentioned in the publications. A consent form and a participant information sheet were sent to participants ahead of the interviews, interviews were recorded only if permission was granted by the interviewees, and the collected data were kept in encrypted university drives and only the researcher had access to them. Overall, ethical standards were followed in all stages of this study, from design to writing up and report.

3.12. Data collection, methods, and techniques

3.12.1. data collection methods

This section highlights the .data collection methods adopted for this study. There are various sources for gathering evidence for case studies such as documents, archival records, interviews, direct observation, participant observation and physical artefacts each of which might have its own advantages and disadvantages. For interpretive case studies, interviews could be deemed as the primary source of data (Walsham, 1995).

Among the mentioned methods, interviews were selected as a primary data collection technique because of their ability to best address the research question, and particularly our interest in individuals' perspectives, thoughts, interpretations and views about the phenomenon being studied. Interviews facilitate the construction of meaning that might be hidden or unseen through interactions between the researcher and the interviewees, enabling the researcher to come across and further explore the complicated phenomenon under investigation (Tracy, 2019). Again, as mentioned in the potential researcher bias section, self-reflection is important to obtain better results prior to interviews. In doing so, researchers can self-reflect by writing down their own obvious characteristics that might be noticed by interviewees and ponder over them before approaching the field. Mock interviews were conducted to make sure the researcher identified potential biases and was consistent and neutral during all interviews.

Semi-structured interview, containing a list of fundamental questions helping to guide and define the area of conversation, has been chosen as a main data gathering technique (interview style). It allows the interviewees to go further and elaborate on their responses (Chadwick et al., 2008). However, cost and time requirements and inaccessibility to participants might be some of the interview drawbacks (Roller and Lavrakas, 2015). In addition, Interviewees may not allow researchers to record the session and if they do, transcribing the recorded interviews might be time-consuming (Walsham, 1995). Most of the interviews were conducted via Microsoft Teams because of the accessibility, time and cost issues.

Yin (2018) Highlights the importance of preparation before collecting data for the case study to proceed smoothly and not jeopardise the case study that includes developing necessary skills, developing a study protocol and other essential skills. For example, unlike laboratory experiments which are rather routinised, high-quality case studies call for an experienced researcher (How to ask a good question ,how to be a good listener etc) not only because qualitative data collection is more complex but also there are other ethical issues involved in data collection phases such as confidentiality and possible conflicts in the field (Yin, 2018). Accordingly, Before approaching the field, the researcher consulted other researchers and colleagues (who had already conducted qualitative studies and were experienced), asking them about their experience in conducting qualitative interviews, and he also interviewed them and received feedback regarding the questions, body language, listening techniques, and generally managing the interview.

There are different ways and techniques by which researchers can make the most of interviews and improve the quality of evidence collection. Making plans and protocols for data collection is important after choosing the cases. Even more, Eisenhardt (1989:538) argues that “the triangulation made possible by multiple data collection methods provides stronger substantiation of constructs and hypotheses.” In order to increase the possible creativity in the study and enhance the confidence in results, using several investigators seems to be useful. Adopting this method causes cases to be studied from different points of view (Eisenhardt, 1989). However, for this study, only the main investigator has access to the data and analyses them. Moreover, to be more effective in the process of data collecting, Eisenhardt (1989) suggests that it is better to take note of every impression occurring during the interview. Because it is difficult to judge what could be useful during the interview. Another key point might be keeping all thoughts for example in the form of memos and also having an informal meeting to share views and thoughts (Urquhart, 2013). Notes taken by the researcher during the interviews were used during the analysis stage.

3.12.2. Individual interviews

For this study, key participants were contacted via different communication channels search as emails, in particular providing them with three documents including an invitation letter, a consent form, and a participant information sheet (see appendix). The invitation letter introduces the topic of the study, and the researcher and briefly discuss the research background. The participant information sheet provides some information on the purpose of this study, research design, how to participate in the study and particularly confidentiality of the content of the interviews and participants' information, potential benefits, opt-in and out to the research, organisation of the research and the supervisory team including their contact details. The consent form is used to obtain participants' written consent in terms of their voluntary participation, Interviews being audio recorded. After participants agreed to participate in our study, the researcher made appointments with participants at specific times and locations based on their convenience, which were either face-to-face or online. The researcher followed the same exact procedure for every participant and asked the same questions in the same order (see appendix).

3.12.3. Transcription and memos

Reporting the fieldwork is of vital importance and it is not particularly reporting the facts, but it is actually an interpretation of peoples' interpretations. For the interpretive case studies, Walsham (1995:79) suggests "the collection of field data should include details of the research sites chosen, the reasons for this choice, the number of people who were interviewed, what hierarchical or professional positions they occupied, what other data sources were used and over what period the research was conducted". In addition, other processes need to be mentioned such as data analysis and iterative processes.

Interviews are recorded to collect the full account of participants, provided that they give consent, otherwise the researcher has to jot down the answers that might result in missing some key concepts. In order to acquaint himself with the data, the researcher transcribed all the interviews manually without using any voice recognition software. Notes (reflections and hunches) were taken in the form of memos and diagrams not only during the interviews but also while transcribing, containing suggestions and clues. Those memos helped in interpreting the data.

3.13. Data analysis, tools and techniques

The data collection phase is followed by the data analysis stage which includes transcribing the data collected via various methods (interviews and documents), analysing the text by thematic coding and using appropriate software such as NVivo in order to elicit meanings and insights, and continuing review of the participants' narratives based on the literature review in order to understand where the extracted frameworks and theories reside within the literature.

According to Yin (2018), data analysis is considered as the core and also the most difficult part of theory building from cases. In this regard, within case and cross-case analysis could be made. In terms of within case analysis, writing up the details and describing them is important and has a key role in creating insights. For cross-case analysis, some specific dimensions could be compared among groups or a pair of cases might be chosen and compared in terms of differences or similarities. Another method might be grouping data based on their collection technique which can be useful in bringing different insights and views into the analysis (Eisenhardt, 1989). "Overall, the idea behind these cross-case searching tactics is to force investigators to go beyond initial impressions, especially through the use of structured and diverse lenses on the data" (Eisenhardt, 1989:541).

Data analysis starts with the data collection phase. Accordingly, Silverman (2015) argues that firstly it is better to develop a detailed analysis (deep analysis) of very small amounts of data ("intensive analysis") which would be helpful in initially grasping a phenomenon being studied. After this stage, "extensive analysis" could be made which is associated with looking at similar features in the whole data (Silverman, 2015). For this purpose, a coding approach is used.

Coding refers to attaching conceptual labels to the data which are developed by constant comparison between data and theory (Urquhart, 2013). Consequently, new theories and concepts would be the result of this comparison. In this sense, it is important to note that the reasoning logic is abductive in this research, meaning that some concepts might come from the literature, unlike the inductive approach. In addition, the role of literature is vital in terms of comparing the appearing theories with extant literature. This constant comparison might result in consistency with or conflicts with the literature. There is an important question of when a researcher should stop adding cases or iteration process. Accordingly, Eisenhardt (1989) suggests theoretical saturation. "[t]heoretical saturation is simply the point at which incremental learning is minimal because the researchers are observing phenomena seen before" (Eisenhardt, 1989:545). In addition, for the number of cases, she also suggests the number between four and ten might be suitable for theory building. However, there is no standard number for this purpose.

Computer-aided qualitative data analysis packs such as Atlas.ti and Nvivo are increasingly used in data analysis that are capable of covering various types of data, particularly unstructured data (texts and videos. However, it's important to note that these tools cannot finish the analysis and researchers themselves have to interpret the output, unlike statistical analysis outputs you can directly use the software output (Yin, 2018). Concepts and relations between variables come out from data analysis and this process proceeds until fitting the theory with data. In this regard, constant comparison of data and constructs will result in better-defined constructs. Generally speaking, the verification of relations and measurement of constructs contribute to the development of hypotheses (Eisenhardt, 1989).

There are various analytical strategies that researchers can apply, however Yin (2018) suggests, as a starting point, that playing with and manipulating the data would be helpful in searching for patterns and insights. Other techniques can include categorising the data in various arrays containing themes and subthemes, juxtaposing two different interviews, putting contrasting categories in a matrix, using visual displays such as flowcharts, and arranging and categorising the frequency of various events (Yin, 2018).

3.14. Coding and thematic analysis

The concept of open coding was introduced by Glaser in 1978. It is a process that involves assigning the initial labels to data, which allows the emergence of various categories and their properties. This study aims to explore and conceptualise open coding by allowing users to interact with the data. The continuous comparison of data sets throughout the study was also carried out.

In terms of using the literature as the important starting point, Walsham (1995) suggests giving some extent of freeness to field data and inclination to reform and revise initial assumptions. This could be useful in helping researchers to explore new avenues and issues.

Accordingly, the goal of open coding was to maintain its open nature and allow the users to interact with the data. In order to do so, the researcher tried to remain as open as possible to the analytical meanings. Through this process, the analysis of the data was able to uncover what was important to the study and provide more analytical direction. Another important aspect of the process was the interrogation of the data, which involved identifying the various categories and their properties.

The goal of selective coding was to expand the scope of the open codes and categories into those that were most relevant to the research problem. The process also involved making important decisions related to the direction of conceptualisation and the strengths of emerging concepts (Urquhart and Fernandez, 2013).

At this stage, the analyst has to make important decisions about which open codes should be used in order to classify the data. This is because the decisions that the analyst makes after having defined the various analytic directions are very important. The research problem was used as the guide to identify the open codes that are most important to the study, and this led to the formation of larger categories. The research problem also informed the selection of the appropriate codes for the selective categories. The coding and data analysis has been carried out manually for this study.

For example, "*But how familiar they are with it", "very aware of that data", and "familiarity with data"* were coded as awareness. In this regard, Awareness is an open code. Once the open coding process finished, selective coding started to scale up the open codes, helping more significant categories and concepts emerge. For example, *Leadership*, *Awareness*, *Responsiveness*, *Cognition*, *Human capital*, and *Social capital* were among the open codes that shaped the selective code Managerial Capabilities. Those subcategories or selective codes shaped bigger categories or themes. For example, Managerial capabilities, Knowledge management, Learning, and Environmental dynamism were under the theme of Dynamic Capabilities. In this sense, it is important to note that the conceptualisation of emerging concepts was directed by the research problem, literature review (constant comparison), and the theoretical lens which was the dynamic capabilities approach for this study. Otherwise, so many other open codes could have emerged that are not necessarily relevant to the research question. The main themes of the study, relevant subcategories and associated open codes are presented in the analysis sections.

3.15. Chapter Summary

This chapter aimed to introduce the concept and purpose of the study, as well as the practical aspects of the study, to the wider field of qualitative research. Through this, the researcher was able to move in a direction that is consistent with the study's primary objective. The objective of this chapter was to provide an overview of the various aspects of the qualitative study. It also answered two of the most common questions related to the study: how the study was conducted and how the evidence was obtained.

The main objective of this chapter was to provide a comprehensive overview of the various aspects of the study, including the design and methods used to collect and analyse the data. It also explored how the data was used to generate effective and meaningful evidence. Chapter 4 provides a detailed analysis of the findings of the study.

4. Chapter four: Findings of the study

4.1. Introduction

This chapter is concerned with presenting the findings of the study. The three main research themes that emerged from the data analysis process and were guided by the literature review were *decision-making, dynamic capabilities, and organisational design.*

As mentioned in the methodology chapter, nine companies were selected for investigation based on purposeful sampling, and the company selection process was stopped when theoretical saturation was reached. Interviewees are labelled with alphabetical letters to keep their identities anonymous. Table 4-1 shows the interviewees' labels and their roles and company sectors.

Table 4-1: Company sectors and interviewees' roles

Company number	Company sector	Interviewees' labels	Interviewees roles
1	Fintech	A	Head of analytics
2	Transport and delivery	B, C, D	Data analysts
3	Consultancy	E	Head of research and analytics
4	Energy	N and P	Data analysts
5	Construction	F	Coordinator and data analyst
6	Energy	G	CEO
7	Telecommunication	H	Data analyst
8	Consultancy	L	CEO
9	Telecommunication	M	Digital transformation project manager

4.2. Decision-making Theme

4.2.1. Introduction

This section elucidates the findings related to the first core Theme, *decision-making*. The other two main research themes, *dynamic capabilities* and *organisational design* are discussed in the following sections, respectively. The findings within these three chapters represent the perspectives of the participants on the evolution of decision-making processes, developing dynamic capabilities to cope with fast-paced environments and organisational design.

The participants' perspectives have been interpreted in light of the research question and objectives. The research question and objectives have informed and helped the researcher in terms of organising the emerging themes and categories. The assumptions made by the researchers during the course of the study guided the interpretation of the data and the categorisation of the findings. The various assumptions that were made during the development of the study, which were in line with the primary objective, provided a framework for the interpretation of the data. This led to the development of new concepts that were beneficial to the research questions.

The theoretical model presented in the literature is shown in Figure 4-1. It states that dynamism can be found at various levels, such as macro, meso, and micro. A holistic approach is required to improve the decision-making capabilities of big data environments. Culture and design play an important role in helping organisations develop the capabilities to make better decisions. The diagram shows how knowledge management and learning can help improve decision-making.

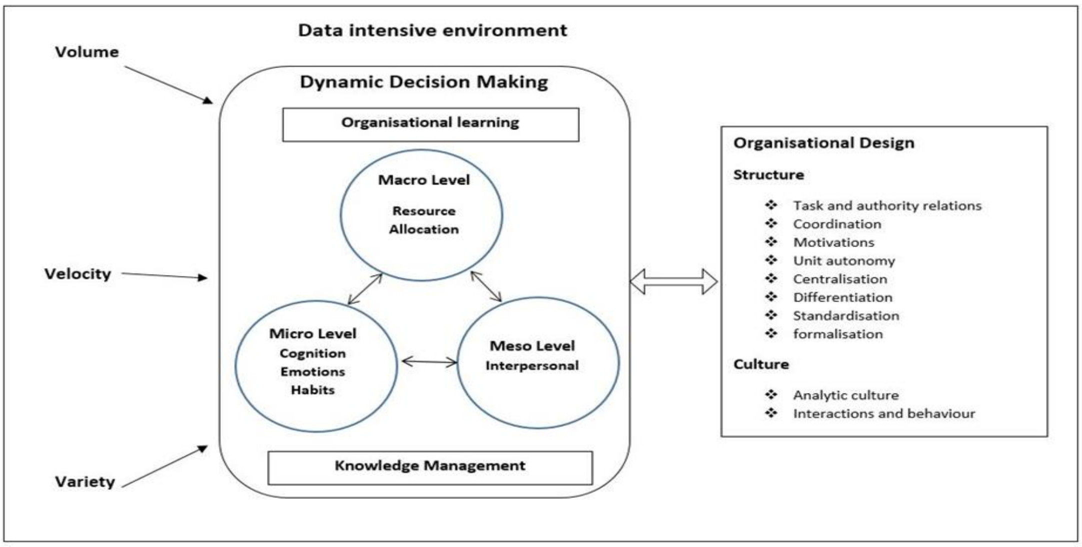

Figure 4-1: Theoretical model emerged from the literature (source: author)

Table 4-2 shows this category theme (decision-making), the related subcategories, and the open codes underpinning the theme. A number of subcategories associated with decision-making range from decision-making styles, including *normative decision-making, intuitive decision-making, and natural decision-making,* to decision-making processes such as *team-processes.*

Table 4-2: An overview of the decision-making theme

Categories	Subcategories	Open codes
Decision making	**Normative decision-making**	Logic and evidence Data analysis Evaluation of information Real-time decision making
	Intuitive decision-making	Feelings Habits Heuristics Intuitive cognitive style
	Natural decision making	Perception Adaptation Complexity (abundance of variables)
	Team processes	Information processing Capacity and flow Responsibility Synergy and collaboration, Diversity of skills and Expertise Conflict of interests Time pressure

4.2.2. Normative decision-making

The first key Category of decision-making is *normative decision-making*. This category encapsulates the participants' perspectives in terms of *logic and evidence*, *data analysis*, *evaluation of information* and *analytical cognitive style. Normative decision-making* illustrates an important decision-making style that participants have used to make certain decisions or contributed to them. Decision-making could be defined as a process that involves formulating goals and choosing the best option for achieving them. This managerial activity involves analysing various options and making a final decision (Intezari and Pauleen, 2017). This category is of high importance in decision-making in data-intensive environments as the *normative decision-making* style draws on logic and evidence that participants have relied on.

The findings show the crucial role of *logic and evidence* in evidence-based decision-making processes. One of the participants in one of the leading companies within the UK that heavily relies on big data analytics elaborates on the impact of real-time data and insights that emerged from the data in making operational decisions. The following excerpt shows how real-time decisions are made based on the collected data and evidence by using mathematical algorithms.

> *"So, we are looking to explore, get better insight from our data to improve that delivery experience along the way for our customers. (…) we want to be making real-time decisions on our data. And that's where the sort of big data and the big data analytics is what we're interested in. So, we sort of get algorithms to make decisions on our real-time process. (…) What we want to move towards is real-time processing, and then make those real-time decisions which are crucial."* (Source: B).

The findings show that *data analysis* plays an important role in supporting decisions. Those decisions could be in all tiers of the organisations. This includes supporting decisions at the operational level for daily and short-term decisions, tactical decisions such as comparing different areas and their performance, strategic level and long-term decisions by looking at the big picture, higher-level decisions by looking at the aggregate summary of the analysis. In the following text, a participant who is a data consultant explains how real-time data and historical data could be used for various purposes by giving examples.

> *"Yeah, so one of the things I mentioned was about how to who to target to cross-sell who to target to upsell products, that would be one decision. You mean, that's right, that is right. Looking at the type of, you know, packages a customer is taking and utilising that would change their decisions. How do we market, the campaigns that would, again, be driven by which customer segment they're trying to market to? So that is, again, they would rely on the decisions about, you know, how do we forecast a particular product we are trying to launch would depend on the sales forecast happening will depend on the data has been. so, all of these decisions they rely on, you know, other than the business, other than other third party factors, they would rely on the historical data as well."* (Source: M).

The findings show that *data analysis* plays a key role in supporting normative decisions. A data analyst in the following passage explains the process of the normative decision-making process as she provides the necessary insights and information for the decision-maker to rely on.

> *"I will do my analysis, give my recommendation by the idea overall. So, I would send it over to her like review it, show her where we're at with it. And then but she would do the official sign-off on it. So, based on what I've reported into her, she will then make the decision, yes or no on what I've said. So, she's the only person to make those decisions based on the insight you get from data basically"* (Source: H).

Similarly, another participant, a data consultant in one of the main phone companies in the UK, highlights the role of data analysis and how insights extracted from data collected from customers' profiles could be used for decisions. It is important to note that those data sets are rather huge coming from millions of customers.

> *"So, if you look into a customer profile, and you see that most of the months, the customer is finishing off its data limit, then you would go and upsell the customer, giving them more access to actually giving them more data. And if they aren't using much of the minutes, then you make the packages so that they, you know, they choose the package which will give them more on the data side. So, this is how the other teams would be using the data to deliver. Then you have the wholesale team would look into their wholesale prices versus the margins and we're getting some usage on the network as well. So, it depends on which team was using the data. They will take the data element of data and utilise it in their way."* (Source: M).

According to the findings*, real-time* and near-time analysis of data is crucial in terms of informing decision-makers to be able to make *real-time decisions.* As evidenced in the below text, failure to provide the right information for decision-makers in a timely manner may affect the business.

> *"if I have to do a big piece of analysis, to inform my board of directors, or my senior management team, my directors, etc, about something, then I have to do it in the time that they can make the right decision, which will then affect the business, because delay can affect the business in a bad way. Yeah. So time, you know, hitting the time is important. And sometimes it becomes a time pressure"* (Source: E).

Real-time or near-time analysis of the data has been frequently brought up by the participants. In the following excerpt, a data expert argues the importance of such analysis in terms of real-time or near-time usage of data for the decision-making processes.

> *"So a big part of the decision-making process is, as something we decide to acquire that data, how quickly are we going to use that data in the form of a marketing campaign, whether that's direct mail, whether that's email, whether that's phone calls, so that big types of big, big part of the decision-making process around acquiring data"* (Source: L).

Evaluation of information is one of the dimensions of normative decision-making processes identified by participants. In this aspect of the decision-making process, decisions are purely made based on the evaluation of the information collected. The following excerpt shows an example of this process mentioned by a data analyst. However, these decisions can either be made automatically by using artificial intelligence and machine learning or by humans as decision-makers.

> *"types of decisions, like commercial decisions, so based on core records that we've got coming in, like International goals, for example, it'd be based on our costs, that like the cost that we would then pass on to an end user and the cost of putting that into say, you had like a call bundle. So, you charge like 10 pounds a month for unlimited calls to the world. So, I base that based on like countries, the cost, and the average usage per customer overall of them to work out if it was financially viable to offer that as a package. So, the commercial, the commercial viability, financial viability of offering that sort of thing."* (Source: H).

The findings show that the *evaluation of information* is a challenge that many businesses can face. This concept is about evaluating the information in the right way (not only analysing the data), in other words, in a way that can be useful for a particular decision.

> *"the challenge that we face, even with that volume of data, is often interpretation and analysing it in the correct way"* (Source: E).

4.2.3. Intuitive decision-making

The second key Category of decision-making is *intuitive decision-making*. This category encapsulates the participants' perspectives in terms of *feelings and habits, heuristics, and intuitive cognitive style.* As discussed in the literature review section, *Intuitive decision-making* mainly depends upon intuition and the decision maker's perception of the issue, which is derived from their experience and feelings.

According to the findings, participants have identified *intuitive cognitive style* as one of the aspects of the intuitive decision-making style. The following text shows that decision-makers might resort to their intuition if they do not understand the data and cannot trust data for their decision-making process.

> *"there may be others who don't know the data well enough to then decide whether they can trust it or not trust it, okay. So, there are people who do not understand or engage with the data. Unless you can understand and engage with the data, you can't make the best decision about whether to trust it or not."* (Source: E).

The findings show that decision-makers use various decision-making styles based on different reasons. This might be because of cognitive style, time pressure, lack of access to data, the abundance of data, and so on. In the following excerpt, a participant argues that time pressure and a need for a quick decision are among the main reasons for resorting to intuition for decisions.

> *"when it comes to like quick and fast decisions, when there is a time pressure, I think they might be using more of their intuition rather than like data."* (Source: M).

The findings show that decision-makers sometimes rely on their *heuristics* for making decisions. In this decision-making process, they usually rely on their mental shortcuts, which are built over time based on experience, learning, and performing various tasks. The following excerpts show that decision-makers using this dimension of the decision-making process tend not to trust data and make decisions based on intuition. As evidenced, they might also argue with the data analysts as they do not trust the insights that emerge from the data. They would argue if the insights from the data are not in line with their perception of the problem.

> *"So yeah, that's essentially a bit quite often is like, obviously, it was perceived as like some little geek in the corner, like don't like that is what you're perceived as if you do sort of data analysis of any sort. So, I'm a geek in the corner. And people will sometimes argue with the things that I've started because to them, it doesn't seem as if it would be right. Okay, so to them, that doesn't seem right. So, they'll argue with that, because they're like, no, that doesn't sound right to me. And I'm like, Okay, well, that maybe doesn't sound right to you, but it's fight on paper. So, you do sometimes have to argue"* (Source: H).

The findings show that although the decision makers, especially at the senior level, trust data, they do not necessarily make their decisions based on the data. Senior management teams tend to use their gut instincts. In the following text, a data consultant argues that not all the decisions taken at the apex of the organisation are data-driven.

> *"I think they trust the data, but they do not 100% use it and have a method of, you know, at the higher management level who are making decisions, they also use their gut instinct. They are not purely driven by the data"* (Source: M).

4.2.4. Natural decision-making

The third key Category of decision-making is *natural decision-making*. This category encapsulates the participants' perspectives in terms of *perception, adaptation, and complexity (abundance of variables).* In reality, it seems that most decision-makers assimilate the concepts of normative and intuitive approaches simultaneously rather than sticking to one specific approach.

The findings show that organisational members' *perceptions* of data can vary, and this influences the way they make decisions. According to the following text, some people are not going to engage with data. The possible reasons for this behaviour are explained in the discussion section.

> *"But you have to accept that there are some people who are not going to be engaging with the data. And many businesses will just accept that and work around it"* (Source: E).

Adaptation

> *"However, there's a lot of mystery around a lot of our bigger data sources. So, people are often happier to use data that they are more familiar with. That is a really big factor in how somebody feels about that data source. If not, they feel they have to outsource that decision."* (Source: A).

Participants have highlighted the abundance of variables as a challenge in decision-making processes which refers to *complexity*. They've raised this issue as the insights coming from various sources of data might contribute to complexities in decision-making processes.

> *"And it's a big challenge. And then again, also looking for patterns. So there is this one data set here. But there is another data set, it might seem that there are some correlations or patterns here, but how do you analyse the two together to identify the correct patterns? It's those kinds of challenges that many small businesses, I think, face. And the reason we face those challenges is because of resources."* (Source: E_1).

4.2.5. Team processes

The fourth key Category of decision-making is *team processes*. This category encapsulates the participants' perspectives in terms of *information flow and processing capacity, responsibility, synergy and collaboration, diversity of skills and expertise, conflict of interests, and time pressure.*

The findings show that many of the participants have mentioned the high importance of team processes in decision-making. However, the role of *responsibility* was highlighted by them as a key factor in making the final call. One of the participants, as shown in the passage, explains the democratic aspect of decision-making and then refers to the role of accountability in that process.

> *"I think that the decision-making process is definitely democratic. But ultimately, the responsibility sits with the team leader of the team manager, right. And it is very important within an organisation that somebody is accountable for the decisions that they make. But from their side, they have to make sure that others are involved in the decision as well or others have contributed to making the right decision. So the decision-making process is democratic. But the final call on whether to do something with or not to do something or take on a project not to take on a project, etc, will probably be the team manager or the team leader concerned, I think."* (Source: E).

In a similar way, a CEO highlights the role of *responsibility* in strategic decisions and plans as the consequences of the decisions will affect the businesses. In addition, he particularly attributes this responsibility to the person in charge of a decision-making team.

> *"So, the strategic plan, which are put in place, ultimately strategic plans, are the hardest decisions to make, because they're longer term, and you've got to, you know, as fast as possible get that right. Because if you don't get that, right, then it affects the whole business, then, especially when you're in charge of like, large teams, especially when you've got responsibilities"* (Source: F).

The findings show that, as shown in the following passage, data analysts play a crucial role as a supporting function in decision-making processes by providing the necessary information for the decision team. This also refers to the *diversity of skills* within a decision-making unit, as team members possess various skills.

> *"Ultimately, we're a support function for the business. But of course, with the data and information we've got, we play a part in the decision-making process. But in effect, there's an operations board and they'll make decisions that can change. But I wouldn't call that a bureaucratic process. So, a decision can be made one day and be implemented the next day." (Source: D).*

Participants have highlighted the importance of *information flow* within teams, which plays a crucial role in decision-making processes. Information flow can be facilitated and hindered by various factors, some of that has been identified by the participants and discussed in this chapter. The following passage refers to trust and openness to share information within teams which would contribute to improving information flow and consequently better and faster decisions.

> *"To add value to a project or to solve a particular problem, you know, you might find your colleague has this nugget of information that can really help you progress a certain element of a project. Solve problems, so, so yes, this is really, really important to have that openness, and trust in your team for facilitator" (Source: P).*

The findings show that the collaborative decision-making process plays a key role in strategic decisions. As evidenced below, a managing director of a company reveals that they rely on a team of five to six to make important decisions referring to the concept of *synergy and collaborative* style.

> *"we've got the management team (…). So, the members of the management team will be part of an annual or biannual workshop where we think about strategy, think about direction. Yeah, so a lot of it comes from the six directors now five directors since we did a partial sale of stuff this year, but a lot of it also comes from our management team. We're pretty collaborative in our style"* (Source: N).

The findings show that, especially in larger organisations, data analysts are not necessarily decision-makers. Instead, the analytics team provide the necessary information as a result of their analysis for the decision-making team to sign off the final decisions. The results of the analysis are usually fed into the dashboards, and therefore decision-makers, depending on their access, use them as decision support. However, according to the findings, some organisations involve their data analysts in their decision-making teams actually to discuss the insights and intelligence extracted from data. In the following excerpt, a data consultant who is responsible for the digital transformation of a huge company discusses the role of the analysis team as mere analysers, not decision-makers.

> *"So they are just providers of how the data and analytics and what is working. it is based on that data analytics piece and the information that is provided as on the result of the dashboard is what the teams make the decision (…) And depending on that the order for the next slot would be made. So how much to water would not be a data analyst's decision? That would be the team's decision. (…) What I am clear on is how they use the dashboard and what that element of the data and dashboard fed into their decision-making (…). Now, the data analytics team does not make those decisions. They just provide the foundation blocks for the teams to make the decision."* (Source: M).

The findings show that where directors deal with familiar markets and data, processing the data will be much easier. However, facing the deluge of new data coming from brand new markets might, data processing individually might be challenging. So, this would call for collaboration and team processes. In the following excerpt, a data expert shows that the teams would have a better information processing capacity by collaborating. This would also result in faster decisions compared to individual decisions.

> *"Internally, those directors will find the process far easier if it's data relating to their existing markets. But if it's a brand-new market that they're trying to target, (…) that involves a lot more collaboration, it involves a lot more meetings, it involves a lot more market research that I provide before we start spending lots of money. for collaboration and team, let's say group decision makings are important factors in this case "*(Source: L).

Participants have also identified the *diversity of skills and expertise* as a key factor in group decision-making processes. A board of directors, in the following excerpt, explains how diversity of thoughts, ideas, expertise, and personalities could contribute to better decisions by challenging various ideas and bringing a wider variety of thoughts to the table.

> *"if you're making decisions as a group, you need people to be able to input their thoughts, their ideas, and then also make room for others. So, we do we make a lot of decisions, I would say collectively. (…) we have different personalities, different appetites for risk, different levels of ambition. So, one of us might have a very high level of ambition, that probably wouldn't be me. So, they might say, Well, of course, we can do that. Yeah, we can go for that. Okay, so I'm thinking, so I'm pulled along by that decision. So, I think you need to have a range of personalities. And people talk about diversity, it is the world's biggest buzzword at the moment. But it's a mind, that just means having a range of different people, different personalities and different backgrounds. Hopefully, hopefully, some diverse experience."* (Source: N).

The findings show that, *conflict of interest* has a role to play in team processes in terms of facilitating the information flow within teams. The following excerpt shows that individuals' personal interests might affect the willingness to share information within teams.

> *"I think, from my experience, it comes a lot to deal with the individual company's organisational culture. With how willing individual employees are no matter what level they are, I want to share data when it comes to all architecture but also how much the individual is willing to, to team work effectively with their, with their peers, like to share that information, so that both party both team members can and can excel."* (Source: P).

The findings show that *time pressure* is one of the key aspects when it comes to team processes. A data analyst highlights the importance of having a team for making decisions, as time pressures and deadlines would impact individuals' perceptions. She also refers to external circumstances such as COVID-19 affecting the decision-making processes by making the external environments uncertain and dynamic. She also mentions the collaboration between team members has also been affected as a result of time pressure.

> *"That would be ideal to have a team. So, there's a lot of pressure on one person, and it is basing a lot on that one person's perception. Because at the moment, although we do have a team we do is because it's again, it's since COVID, we've been so so busy, that we've not been able to really collaborate on it as much as we should have done."* (Source: H).

4.3. Dynamic capabilities Theme

4.3.1. Introduction

This section represents the second core category, *dynamic capabilities*. This core category (theme) is concerned with the various features and dimensions of *dynamic capabilities* within the studied organisations identified by the participants.

Table 4-3 shows this category theme (*dynamic capabilities*), related subcategories, and open codes underpinning the theme. A number of subcategories associated with *dynamic capabilities* range from *managerial capabilities*, *knowledge management, and learning to environmental dynamism.*

Table 4-3: An overview of the dynamic capabilities theme

Categories	Subcategories	Open codes
Dynamic capabilities	**Managerial capabilities**	Leadership Awareness Human capital Social capital
	Knowledge management	Articulation Constructive collaboration Exploration Codification and Knowledge Exchange
	Learning	Experience Reflection Interactions Training Routines and process Dialogue
	Environmental dynamism	Regulations Industry and competition Time pressure

4.3.2. Managerial capabilities

The first key Category of dynamic capabilities is *managerial capabilities*. This category encapsulates the participants' perspectives in terms of *leadership, awareness, human capital, and social capital.* In the DC approach, managers have a key role as decision-makers by defining and designing the competitive position of their firms (Kor and Mesko, 2013). Dynamic managerial capabilities play an important role in fitting the organisational competencies with dynamic environmental conditions. Accordingly, "Even the best-designed dynamic capabilities, however, cannot succeed without seasoned managerial judgement" (Day and Schoemaker, 2016:75).

The findings show that the participants have identified *leadership* as one of the key aspects of managerial capabilities. The following point of view reflects the leadership's role in motivating organisational members to understand the importance of data and put trust in that. As evidenced, leaders' role in explaining the benefits that data might bring about has been highlighted and leaders' support can change individuals' attitudes towards the evidenced-based decision-making process.

> *"leadership theory will say, there are some leaders who are dictatorial, there are some leaders who are inclusive, and then there are some leaders who are, you know, consensual decision makers and that sort of thing. Now, the approach of what I said, which is you have to understand and accept that there are some people who do not trust the data (…). And I think it is the duty of the organization to explain to them that the data is there to help them; it is not there to take advantage of them, it is for them to take advantage of the data. We should do everything we can, as an organisation to help motivate those individuals."* (Source: E).

The findings show that *awareness* is a key factor that overrides decisions. In the following excerpt, one of the participants highlights the role of awareness in enhancing the decision-making process.

> *"But how familiar they are with it - if we were to say, "right, we're going to look up our CRM system," they are very, very aware of that data. They often pull their own reports off that data and they have at least some involvement in it. Some of the more interesting things that you can do with that data - they might not have the tools to do that. But they are much more comfortable with that as a data source. I think sometimes, just familiarity with data is a factor that I never anticipated. But it's something that definitely overrides in decisions."* (Source: A).

The findings show that the awareness and deep understanding of the business would contribute to reaping the most value from data and analysis. In the following text, a participant argues people with a good understanding of the data and the organisation can harness the most value from data. This is key, as this would facilitate the communication, perception and interpretation of data across the organisations.

> *"Always, I think reaping value from big data, always individuals, analyst analytics, because business and corporate, they have a certain view, they wouldn't know how to extract. So the extraction lies very much on the analyst. And it is a bit of both. And I think people who are very, very well placed to be on both sides of the fence would drive the maximum value."* (Source: M).

Participants have regularly identified the role of *Cognition* in managerial capabilities. Perceptions, skills, thought processes, experiences and knowledge acquisition techniques of people vary, resulting in various cognitive capacities. The following excerpt also shows individuals' capabilities in assessing the effectiveness of various decisions and metrics might be different depending on their cognition.

> *"So, for the individuals, it is about having the capability and the knowledge and the skills to think about both, you know, the actual work that they do, whether it*

is creative work, or you know, routine, repetitive work, but then also bear in mind, the ability to assess the effectiveness, understand the metrics, etc, for the activities that they do. So from an individual's point of view, it is all about having the skills and the knowledge and the opportunity to apply it correctly." (Source: E).

The findings show that understanding the big data being used in decision-making processes would influence the quality of data that is collected. This refers to *human capital* as one of the managerial capabilities identified by the participants. In the following text, a data expert expresses his account of the relationship between the managers' perception and understanding of the data, with the quality of the data they collect. A deep understanding and knowledge of the data and its capabilities in conjunction with the data required for the current business could contribute to opening new doors for new customers.

"I think the more they understand about the data they're acquiring, the better the quality of that data. So, if they are requiring data that relates to their existing business model, so they want more of the same. So, that's not good development. So, they are after more customers and more clients within the same area that they currently operate within, then the course is going to be better, because they know exactly what sorts of data they need. It's just going to be data relating to new prospect, rather than existing clients." (Source: L).

Participants have regularly highlighted the role that experience plays in shaping managerial capabilities. The following excerpt identified by a data analyst shows how experience and learning from past experience would shape and influence cognition and consequently future decisions.

"the system's making a decision based on the knowledge that we've learned. Yes. So if a person makes a decision, they'll make a decision based on past knowledge.

> *And if we can capture that knowledge, then we can put the decision in inside the system."* (source: B).

Social capital is another selective code identified by participants in terms of managerial capabilities. In the following excerpt, a managing director argues the crucial role of interacting with other team members for decision-making purposes.

> *"I would say it's more about how they think within a group. You know, how they ensure that they input their own view, how they interact within a group. And also, you know, knowing when you can make a decision based on pretty good information"* (source: N).

4.3.3. Knowledge management

The second key category of dynamic capabilities is *knowledge management*. This category encapsulates the participants' perspectives in terms of *articulation, constructive collaboration, exploration, codification and knowledge exchange.* The concept of knowledge management is becoming more prevalent due to the increasing number of employees who are knowledgeable about an organisation's operations. This is because information technology tools and the availability of people with the necessary skills to manage and store data have made it easier for organisations to keep track of their information. The concept of a knowledge-based view is also a development of the firm's resource-based view (Easterby-Smith and Prieto, 2008). The concept of knowledge is a fluid mix of multiple perspectives and experiences that can be used to evaluate and incorporate new information. It can be embedded in various forms of organizations' operations and practices. For instance, documents can be used to enhance the efficiency of an organisation's processes (Thomas H Davenport and Prusak, 1998).

There are various ways by which knowledge gained from data is shared between organisational members. *Knowledge* a*rticulation* is among the concepts identified by participants. The following evidence shows how knowledge is being shared which involves conversation and extraction of knowledge.

"At the moment, we can share data depending on who is requesting it - this might be on an ad-hoc basis. So, if there's a report that you need to make a decision about, you might come to our department and say, "I need some data that will help me understand this problem". Depending on what that is, we will probably just surface that data up to you." (Source: A).

The concept of *constructive collaboration* has been identified as one of the most important dimensions of knowledge management by which collective knowledge can be made available within the organisation. Participants believe that by using collaboration, they can not only share the extant knowledge but also learn from others and update the extant knowledge. This is evidenced in the following passage.

"In terms of sharing, we use lots of different methods. Sometimes we have sharing where people can collaborate on different data sources or put it somewhere such as SharePoint, which we have really locked down. You have interactive data, where people can ask questions and live updating where we can make changes and see it displayed." (Source: A).

Exploring knowledge is one of the key concepts identified by participants with regard to knowledge management. According to the findings, participants have repeatedly mentioned the aspect of knowledge seeking (exploration). In the following excerpt, the participant reveals how they seek new knowledge to improve and optimise the current processes in place and also build on the extant knowledge they have.

"Big Data we're looking at now is about driver activities. And it was some of that driver activity to gain to get to improve our ETAs and improve the scheduling of our drivers' routes. That's what we're looking at at the moment. we're not quite there where we're investigating what we can capture. And how can we improve that optimisation to make to build that knowledge" (Source: D).

Participants have mentioned how data is being codified and shared within the departments via formal mechanisms such as dashboards that facilitate data access. However, they have revealed access to certain data depends on employees' right to do so, meaning not everyone can access every data they want.

> *"all the data is shared, we've got access to our systems, our internal systems, everyone can view the data. And besides the sort of headlines and some reasons, dashboards they can all be viewed and then shared throughout the organisation dependent on your access rights. So, if you're in a particular region, you can see your region's data, but you cannot see another region. (…) so, it is controlled in that way. But we're quite transparent with our data across the organisation."* (Source: B).

The findings show that the development of *knowledge management* capabilities is crucial to information communication between managers and data analysts. In the following excerpt, a data analyst argues that looking at the big picture when analysing big data is of high importance. This is because looking at, analysing, and communicating only smaller chunks of data would not communicate the insights effectively and the aggregate summary of the data should also be considered in order not to miss key insights embedded in the data. Taking a bottom-up approach is key in knowledge management and information communication.

> *"I think the development, it's massively important, because a lot of the things you would never pick up on until you looked at it from a big data point of view, because if you just looking at it on a small, small scale, you'd never noticed a lot of the things you'd never pick up on it, you'd never, you'd never go down, like, go down the route that we have gone down from looking at it from such shifts or like higher level on it. Knowledge Management, we can share it with them in almost bite-sized chunks, which we would not be able to without having the same overviews. Because otherwise, you would have one still thinking like, this is my experience. And everyone just sees it as their experience. Rather than saying like,*

> *this is your experience in amongst all of these experiences, so you can see where you fit, and you can see how that fits into everything else."* (Source: H).

The findings show that organisational members are using various methods to share explicit and implicit knowledge within the organisations. Formal mechanisms such as the codification of knowledge that emerged from data are among the standard ways of sharing knowledge identified by participants. In the following passage, a data analyst expresses how they share the created knowledge within and between departments using formal channels such as documents and dashboards which makes access to the knowledge for everyone easier. She also refers to some of the visualisation techniques that are used to present the information in a simpler and more manageable way.

> *"once we've got something pulled together, we will then share that with every other department that could need it's an operational, sales finance, customer service, I guess it's all about like an overview on it. And but it will be shared between all of the other departments so that they can then read it, they can see it, but by then we've put it into a manageable format. Rather than being like, yeah, they go look at it. And then just being like this is numbers on the sheet. So, use for more channels, your documents the documented you try and put it into like a graph or a chart that people can visualise it seems more manageable"* (Source: H).

Participants have also highlighted the key role of knowledge exchange between members in terms of access to the results of the analysis. A data analyst argues that sharing the results of the analyses would enhance the awareness of the employees in case they need the information.

> *"There's a lot of things that could be good been changed, but not necessarily. Such as more accessibility to data yeah. For everyone make it accessible in every way that you could possibly need it. Because Yeah, we are on the dashboard, but it's not available to everyone."* (Source: H).

The findings show how digitalisation has revolutionised the way knowledge is shared between members of the organisation. A participant in the following excerpt explains how this process of sharing knowledge and information would be helpful in terms of ease of access and also access to real-time information that can be updated in a real-time manner.

> *"So it was very much like, on a disk, people would share information. But with everything now becoming more digital, we use SharePoint, you know, it's there, you can, you know, make an auditable trail of the documents you put up, you know, you can attach comments, you know, you can see when something was changed. So, that is kind of really changed the way we get all our documentation"* (Source: F).

The findings show that, not only *sharing knowledge* between departments is of crucial importance, but also it is necessary within teams to facilitate information flow and quick response to external stimuli. In the following excerpt, a participant explains and emphasises how knowledge sharing within a team whose members share a common objective can contribute to getting to the destination easier and faster.

> *"I think, yeah, it's really important to have that knowledge sharing within your team. Because at the end of the day, you all have a common objective, in your review, or in the same building or in the same place, and you're trying to deliver, really, you know, in our industry, we're trying to deliver high quality solutions to clients. So, you're in the same boat, if you like. To get to the destination easier and quicker. You need to have that knowledge sharing without a doubt"* (Source: P).

The findings show that the advent of big data and large data sets have massively changed the way organisations operate as they are, in nature, dynamic entities and change to keep pace with the increasingly dynamic environments. In doing so, organisations have developed their capabilities such as knowledge management capabilities. Some organisations have implemented enterprise systems to tackle the silo effect and improve the integration and connectedness between departments. In the following text, a participant reveals that data management has massively improved as a result of migrating to an integrated system which facilitates data analysis and sharing of information. In this case, data, information, and the results of the analysis could be accessed across the organisation by using dashboards.

> *"You know, customer base, how much are they? And it was, it was quite crude as the big data and the network usage data came through the level of information that was requested in the dashboards. Because you could see a lot more information from there."* (Source: M).

Two forms of knowledge have also mentioned many times by participants including both *tacit knowledge* which is accumulated in the minds of organisational members as they go through different experiences, and *explicit knowledge* which can be extracted directly from hard data. These two forms of knowledge are increasingly used in the context of knowledge management and information systems. This is evidenced in the following passage.

> *"And you know, in Information Systems, we talk of knowledge management quite a lot. Yeah. So, there is explicit knowledge and tacit knowledge. And, and we are looking at hard data, we are often looking into explicit knowledge. But in the case of many people in their heads, they have a lot of tacit knowledge."* (Source: E).

4.3.4. Learning

The third key category of dynamic capabilities is *learning*. This category encapsulates the participants' perspectives in terms of *experience, reflection, interactions, training, and dialogue*. Like humans, organisations use learning tools to collect and improve their knowledge. These tools can then be used to improve the efficiency of their operations by conducting experiments and collecting customer feedback. Through learning, businesses can adapt to their environment by implementing new business processes and changing their management decisions. The process of organisational learning is a process that involves learning how to respond to the environment. It can help organisations survive when they encounter challenges (Laudon and Laudon, 2020).

Learning is among the most repeated concepts that participants mentioned. The findings show that there are various ways by which organisations and the people within them can learn. One of the methods is training. A head of analytics reveals how she felt the need to acquire new skills since working with big data to be able to manipulate the data. This is evidenced in the following excerpt.

> *"When I first joined the business, I had used lots of different tools. We had different tools and I'd never used things like Microsoft SQL server, or PostgreSQL. I learned lots of query languages to try and actually manipulate that data. So, there was definitely a learning exercise."* (Source: A).

In a similar way, another participant has expressed the need for training on the ground that conventional techniques and methods may not be sufficient enough to deal with big data.

> *"So I have been working with database systems for many years. So personally, for me, getting into the next step was not very difficult. Okay, because the fundamentals are something that I am familiar with. That doesn't mean I know all the latest tools. So for example, you know, the big trend now is to use tools like Tableau for the visualisation and the presentation of big data. Those are things that I have had to go and even get training for myself"* (Source: E).

For new members of the decision-making teams, the following text shows that foundational training would be crucial in terms of familiarity with the routines and processes in place. As evidenced, this could be achieved by formal training that one of the team members or senior management team delivers.

> *"For new, probably not just for senior management but for even new starters, you know, they need to, they need to get up to speed with the current, you know, work processes and procedures of the particular company or in-house procedure. So, and as part of that quite essential feature would be, you know, how they are expected to be managed and appropriately received and stored internally and externally. So, I think all new starters, regardless of their experience level in the seniority will need to go through that foundational training, formal training"* (Source: P).

Training is not the only aspect of learning. There are other dimensions to learning, among which is *interactions* with other members of the organisation which contribute to learning. The findings show that, apart from the technical aspects of the analysis which is of high importance, interactions with other teams and members would be helpful in terms of learning new skills and also how to communicate the insights gained from data to decision-makers. In this regard, the following passage highlights the role of getting to know different teams and having open conversations with them.

> *"I'd say, in terms of how you interpret that data, that learning was very much getting to know the different teams and having that open communication to understand, not only what your level of understanding of the data is and how you might be able to manipulate and interpret that and actually analyse it, but also to the level that you have to be able to communicate it."* (Source: A).

There are various ways by which learning could be achieved such as *reflection.* According to the findings, many participants talked about the learning process that comes from reflection. The following excerpt represents the selective code *reflection* as the participant highlights the key role of reflection with regard to resource allocation and looking how those strategies were effective in the past and learning from them.

"And then once you understand the analytics and the findings, you can make a decision as to the effectiveness or the lack of effectiveness, and then you start fine tuning your next marketing activity (…). So how do we change our next marketing campaign to take into a learning from the past, okay. And I think that is one of the big factors that many organisations will have to learn is to understand, you know, whether it is marketing, whether it is financial performance, whether it is the, you know, the effectiveness of the resources" (Source: E).

The findings show that *dialogue* has a key role in not only sharing knowledge, but also helping individuals with generating new ideas and reflecting on them. The following text shows that constructive dialogue can be extremely important in generating new ideas, sharing thoughts, and learning from other members of the organisation in a short period of time in comparison with other learning methods discussed in this chapter.

"you know, some people are very quick decision makers. But others will want some more time to understand the data, you know, to think about it, to mull over it, and then come up with a recent decision. But because of the pace at which the business will move these days, and you constantly have to make quick decisions, dialogue is extremely important. Because you know, you, you don't generate the best ideas unless you talk to others you want within the organisation. I think that is extremely important, because I might have a wonderful idea. And he might seem to be great, but when I speak to you, you will say, actually, have you considered this" (Source: E).

Another participant also highlighted the role of *dialogue* in communication and learning. In the following text, a data analyst explains how she prefers to talk informally about the matter rather than just sending formal documents. This would help personnel to communicate in a faster and easier way, and share ideas and thoughts, and learn from them.

> *"But I think to get other people onside with what you're saying is a lot better to talk to someone rather than send them something and then be like, this does not look right."* (Source: H).

According to the findings, *experience and performing tasks* have been identified as dimensions of learning by participants. In the following excerpt, a data analyst explains how experiencing and performing tasks over the years has contributed to learning skills and building trust towards data and insights emerging from that.

> *"kind of been doing it for quite a long time now. So, a lot of roles I've had have had the same sort of not necessarily the same subjects, but the same sort of way of doing it. So, I'd say probably started doing things like that when I was like, 19. So I've been doing it like 11 years, really. So, I think at first, I was way more questioning of it. And now I'm more confident and I will look at it more like fact."* (Source: H).

The fourth key category of dynamic capabilities is *environmental dynamism*. This category encapsulates the participants' perspectives in terms of *regulations, industry and competition, and deluge of information.* Business environments are getting increasingly complex and fast-changing due to different factors, specifically advances in data science, information and communication technologies (Grable and Lyons, 2018).

According to the findings, many of the participants have brought to the fore the implications GDPR, which came into law in May 2018, has for their businesses. They identified that the way they collect data, analyse it, and share it has been influenced significantly to make sure they comply with the regulations. The following passage shows that when GDPR was first applied, people within organisations were trying to make sense of that and also make sure to share the data with the right person.

> *"If you look at some of the data protection laws, there have been lots of crackdowns on how data is shared. For example, when regulations, such as the GDPR first applied to our business, people were much more nervous about the way the data was shared. Which, obviously, we should be, and we have to make sure that all data shared with the correct purpose."* (Source: A).

In addition to the previous accounts of the participants about the regulations, another participant (a data expert), argues that the introduction of GDPR has brought about lots of challenges for organisations such as difficulties in terms of big data acquisition.

> *"But there's a key difference between acquiring data, which then belongs to you when you can use that data however you wish, or having access to that data. But that still belongs to the provider because of general data protection regulations. So, a lot of providers I work with nowadays, do not ever hand over data"* (Source, L).

The findings reveal that government policies and regulations can influence a particular industry sector or how organisations operate and collect data. The following excerpt shows that companies are monitoring the external environment constantly to be aware of the most recent changes and regulations in order to be able to act accordingly. In doing so, they will check both background data and if needed, collect new data immediately.

> *"So one of the things that we will look to do is to understand (…) what the government's policies are, we will then have background data that we may have already gathered, or we will then quickly gather at that point of time, and try to understand how an announcement that the Chancellor makes in the budget will affect a particular business or a particular industry sector"* (Source: E).

A head of analytics talks about the data industry and associated waves and changes. The findings, according to the following excerpt, reveal that data is increasingly becoming an important part of many businesses. She also refers to the competitors and how they describe themselves which alerts other competitors that they need to be aware of the contemporary changes in the industry to keep pace with those waves.

> *"(…) there have been so many waves within the data industry and within our business and there's more and more things if you look in fintech in general. Data is becoming much more at the heart of many of the businesses there. As soon as you start seeing competitors saying they're data-driven and that's one of the ways they describe themselves, you start to take note and say, oh should we be doing that?"* (Source: A).

In a similar way as mentioned above, another participant argues that the power of data and analytics is increasing and can influence the competition in the market. As evidenced in the following text, data and analytics can be a source of competitive advantage. It is also highlighted that this can have important implications for many organisations regardless of their size.

> *"even the smaller organisations will need to wake up to the power of data, and analytics. And the decisions will have to take into account the full gamut of data that is available to them. Because otherwise, the competitor will. Yeah, they always do that. So, that is a competitive advantage that will be available from best use of data. Or better use of data."* (Source: E).

The findings show that the participants have brought to the fore the importance of time pressure with regard to keeping pace with the external environment. The time pressure in the decision-making process has been discussed in the decision-making section. The following passage shows how important effective communication with the external environment and time management are in terms of reaping value from data.

“Because we use a lot of economic data, the time is an important issue. Okay, I'm coming to the time pressure point. And the reason for that is if we don't hit the news, or if we don't hit the outside world through our own external communication channels with the data quickly, then we lose value and impact.” (Source: E).

4.4. Organisational design Theme

4.4.1. Introduction

This chapter represents the third core category, *organisational design*. This core category (theme) is concerned with the various features and dimensions of *organisational design* identified by the participants.

Table 4-4 shows this category theme (*organisational design*), related subcategories, and open codes underpinning the emerged theme. A number of subcategories associated with *organisational design* range from *organisational infrastructure, human resources,* and *structure* to *organisational culture.*

Table 4-4: An overview of the organisational design theme

Categories	Subcategories	Open codes
Organisational design	**Organisational infrastructure**	Storage IT Technological challenges Data capture
	Human resources	Awareness of the needs Talent management Recruitment
	Structure	Moving capital Organisational Communication and Information channels Centralisation Formalisation and Socialisation
	Organisational culture	Openness to change Power dynamics Analytical culture Beliefs

4.4.2. Organisational infrastructure

The first key category of organisational design is *organisational infrastructure*. This category encapsulates the participants' perspectives in terms of *data storage, IT, Technological challenges, and data capture.* An information technology (IT) infrastructure is a type of shared technology resource that enables a firm to provide its customers with the necessary information systems (Laudon and Laudon, 2020). This includes hardware, software, and services that are shared across the organisation. It also enables the firm to manage its internal processes and serve its customers.

The findings show that the organisational infrastructures, mainly IT infrastructures, have played a key role in supporting business strategy and decision-making. In the following passage, a data consultant in one of the biggest companies in the UK, discusses how the captured data could be delivered to multiple teams and, based on their needs, could get various insights from the data. In addition, she gives an example of how the extracted insights could be used for decision-making.

> *"the report was delivered to multiple. So we had the products team, we had the sales team, we had, you know, the insights analytics team, who would look at it the usage team. So some of the data would be different to the different teams in terms of how they would use it. So, for example, the sales team would use the data for commissioning their agents. So they would, you know, the agent would submit a commission invoice. And to pay the agent's commissions, they would use the sales data to do that. So, then they would use the same to do forecasting the same state and look at the previous data and then do forecasting. So that is how the same team would be using it. The product team would use the data in the sense of how the usages are happening on the different products."* (Source: M).

The findings show that the advent of big data has influenced *organisational infrastructure* in terms of capturing, organising, cleaning, analysing and disseminating information within the organisations. In the following excerpt, a data analyst talks about the increase in the amount of data they're capturing.

> *"Well, the volume of data that we're capturing has certainly increased over the years"* (Source: B)

Participants have repeatedly mentioned how they capture a massive amount of structured and unstructured data from various sources and integrate it into decision-making processes. The following passage highlights a comment from a member of analytics talking about some of the various ways in which their company collects information from either customers or employees and feeds the information to the senior decision-making team.

> *"So, we're continually capturing information from our customers, from our consumers. We built something within our app called Design Space for customers to be able to feedback on their thoughts. And we've implemented a couple of ideas from there. And then for employees, we've got something that we call where WOW where, for people to say what ideas they've got, and we collect ideas that way, and the board will review it and decide whether we implement. We've got various ways in which you capture information."* (Source: B).

And another participant also discusses the various sources and types of data they're dealing with.

> *"The data that we use is economic data. So, it will have open data that comes from various government departments to have data that comes from the Office for National Statistics. But more importantly, to have data that we collect on our own, that could be through a combination of surveys, it will have some qualitative notes, etc, that we add based on our discussions with different people. And then proprietary company information that we may have access to. So, it's a combination of various things"* (Source: E).

The findings reveal that companies are using various tools and technologies to analyse the collected data. The following excerpt reveals some of the tools and also *technological challenges* that unstructured data brings about.

> *"And my role, and my team's role is to analyse all of that data we use. We use SQL servers, we use Excel, we use statistical tools, etc. to analyse and interpret that data. So that's primarily what we do as within the team is mainly structured data, even SQL data, or it may not be structured data. And that's one of the biggest challenges that I have"* (Source: E).

Participants have talked about how important it is to capture real-time data. As data is not necessarily collected automatically via artificial intelligence or other techniques, there might be a team of experts needed for the acquisition of data. In the following text, a data consultant in one of the prominent phone companies in the UK explains how a team is responsible for the acquisition and dissemination of big data for other areas of the organisation where needed. This, in addition, highlights the flow of information within organisations.

> *"So, within the data reporting and control, we never worked directly on the production box, because that would, that would be made up the performance on the production system. So there was an acquisition team, which would real-time, I think there was a threshold, I'm not sure how many officials were, would put, would put the data into the Big Data box. And then the teams would pick up those data and write ETL to create the logic and data table needed for the analysts. And the analytical workflow, the data reporting guys to work through them."* (Source: M).

A data analyst highlights one of the technical challenges they face while analysing big data. According to the findings, one of the technical challenges is the increasing computational power required to handle the massive data sets.

> *"biggest challenges would be laptop freezing. Like that's honestly, my biggest challenge is my laptop freezes up, because I have so much data running through at once. So once I've pulled it through, like SQL or something like that, that's some sort of reporting. And once it's through that, I will tend to try and put it into a CSV file. And save that for easy manipulation in Excel. Yeah. And yeah, freezing up. Difficult, But that's a lot of data for Excel."* (Source: H).

The findings show that organisations face some technical challenges in terms of handling large data sets. This is because of the nature of these data sets as they are being produced in real-time, have got a massive volume, sometimes are complex, and are coming from various sources. In the following text, a participant emphasises some of the technical challenges and time pressure that they have been experiencing during the data analysis phase. Apart from the technical challenge in terms of the analysis, interpreting and communicating the results of the analysis is another important challenge that has been experienced. The communication of the results of analysis has repeatedly been mentioned by data analysts and other participants.

> *"Yeah, it was always the processing time. It was, you know, challenges. I think more on the technical side of the big data, I was, in fact, close to the technical side, because I wouldn't be able to say, but most the time, I felt the team had issues in terms of performance, running the Big Data queries in the block that it needs to be produced. That way, I would say the challenges were on the technical side on a business side, few times, he had challenges in terms of, you know, interpreting between the business and actually laying it down in the way they want to see it."* (Source: M).

4.4.3. Human resources

The second key category of organisational design is *human resources*. This category encapsulates the participants' perspectives in terms of *awareness of the needs, talent management, and recruitment.* One of the most critical factors organisations consider when implementing a data management strategy is talent management. This is because as data are getting cheaper, data analysts are becoming more valuable. The importance of having the right HR capabilities is acknowledged by Mishra et al. (2018), who argue that this can help companies attract and retain the best talent. Besides identifying and developing the ideal employees, HR also contributes to competitive advantages by assisting companies in improving their knowledge and skills. This is because some of the tacit knowledge has accumulated in the employees' minds, and on the other hand, less qualified members can be a barrier to innovation (Mishra et al., 2018).

Participants have repeatedly emphasised the importance of recruitment of skilled staff, and at the same time, they have mentioned the challenges this might bring about. The following excerpt shows that there's a shortage of skilled data analysts and scientists and therefore they come with a high price. In addition, as evidenced below, they might be able to help organisations with analysing the data, but they may not be of much help in terms of interpreting the data to get the correct information for particular decisions. Therefore, this highlights the importance of talent management and recruitment within organisations. Participants have also mentioned it is important that data consultants have gone through the correct process to arrive at that data analysis, and it is the business's responsibility to make the final decisions as the consequences will affect them, not the data consultants.

> *"If you get a big data consultant or a big data member of staff, because it's a skill set, which is very short, it comes with a very high price. Yes, yeah. And I have met independent consultants, who charge up to 1000 pounds a day, Okay. And what they will do is they will help you put the datasets together, they are now still going to help you interpret the decision. Just putting them together, coming up with some views, some dashboards based on the data, you know, they will help you with that, or in some cases, statistical analysis of the data, they can help you with all of that. But they want us to be able to help you interpret the data in the correct way"* (Source: E).

4.4.4. Structure

The third key category of organisational design is *structure*. This category encapsulates the participants' perspectives in terms of*, moving capital, organisational communication and information channels, centralisation, formalisation and socialisation.* The internal design of the organisations is one of the influential factors in facilitating information flow, which is a key part of decision-making processes (Lewis and Fandt, 1989).

The findings show that there are various *communication and information channels* by which organisational members can effectively communicate and share knowledge and thoughts to learn and make informed decisions. Both formal and informal communication channels have been identified by the participants in this regard. The following passage highlights the importance of dialogue as an informal communication channel that could be used to facilitate the flow of information within the organisation where needed. In addition, this does not mean formal communication channels such as formal meetings are not important. This evidence shows that both channels depending upon the circumstances, could be equally effective in terms of information flow and responding quickly where needed.

> *"at an organisational level, at the corporate level, I think dialogue is extremely important. Because that's when you get the best implementation of the decisions that you make. So, for you is like mainly, like informative channels that are informal and formal channels. (…) we have to do regular briefings for our customers, our members, you know, we do regular briefings for local government offices. (…) So, we have those regular things to external people. But we also have internal regular briefing sessions for our managers and directors. So that's the main like collaboration for different current departments. So, most department managers will be there (…). So those are formal channels. But relying exclusively on formal channels is not enough. Because you might have you know, let's say there is a weekly meeting of all the department managers, and it is for it is every Wednesday, but what if something happens on a Friday and you have to respond quickly to it. So informal channels are just as important."* (Source: E).

According to the findings, the concept of *communication and information channels* and the associated challenges have repeatedly been mentioned by the participants. In the following excerpt, a data analyst reveals the challenges he's witnessed within the business regarding communication.

> *"to implement a change to communicate it to everyone inside the business is the biggest challenge, the actual technology can be relatively straightforward. We can have issues with devices and communications. But, you know, generally those can be overcome. It's the challenge of the users using it effectively and has been able to monitor that they're using the tools correctly. And that's sometimes a challenge."*
> (Source: B).

Another participant has expressed a similar concept mentioned above as many businesses are still struggling with regard to integrating and communicating the collected data into their decision-making processes.

> *"we are constantly speaking to other businesses. And many businesses are still finding it difficult to integrate data into their decision-making process."* (Source: E).

Organisational communication has received the most attention among participants in terms of an important aspect of organisational design. As evidenced in the following text, another participant has also highlighted communication as a real problem in terms of information flow.

> *"They never seem to fully communicate what's happening in terms of information flow. Yeah. So, people aren't aware of, you know, everything that's going on with, you know (…). So, that that is, you know, one of the real problems"* (Source: F).

A head of analytics highlights how a business can heavily rely on a particular person's skills to get insight from the data to make evidence-based decisions, referring to the concept of *centralisation*.

> *"Sometimes, I'll be asked to run a report on a database to say how customers are using our product. But they are then relying very, very heavily on my interpretation of that data because of the tools that we have to use."* (Source: A)

According to the findings, the impact of big data on organisational structure in terms of automating the processes has been mentioned by the participants. The following excerpt reflects the views of a member of analytics who believes that by integrating big data in decision-making processes through using artificial intelligence and machine learning, they can automate some of the decision-making processes within their business.

> *"(…) data will enable us to automate things in the future. So whereas you automated something physical, like building a car, you know, automating jobs of knowledge workers, who are making decisions, to, to act on within the organisation, for example, planning, planning within our organisations, or the people involved in that (…), you could potentially automate that process, because it's the knowledge that they're applying to data, and to come up with a solution. So that's where your artificial intelligence and machine learning come in (…). What if I can capture that data in the background and understand and apply that to our planning process automatically? (…) So I think that can be applied to our business."* (Source: C).

The findings show that, participants have identified *moving capital* as one of the aspects of the organisational structure. In the following text, a data expert explains the importance of the commitment of decision-makers in resource allocation in terms of data acquisition, or in particular, quality data acquisition. He has considered this as one of the challenges in data acquisition for decision-making processes.

> *“the key challenge there is around how do we convince decision makers within our within our client companies to commit the spending a respectable amount of money to gain that data, because unless their budgets too realistic, then they're not going to get the data they want. They promise that they have to be reasonable around their financial commitment towards gaining the data that they want because quality is everything over quantity, in my view. And so that is a key challenge, that's a conversation with these mysteries, leaders and decision-makers around what commitment they are willing to make in order to get the right data that they will report.”* (Source: L).

The findings show that informal ways of communication in conjunction with formal channels of communication and socialisation could be helpful. It refers to the selective code of *formalisation and communication.* In the following excerpt, a data expert talks about how to share information internally and even externally, highlighting the importance of informal ways of communication between decision-makers.

> *“there are a lot of data and its policies, certainly, in recent years sort of become far more detailed than they used to be in terms of how you've shared information internally, and also how you share information leaving the business and going external. So I don't believe there needs to be a formal structure around the use of data. But also, there needs to be a lot of informal conversations, and certainly between decision-makers around just the general acceptable use of how you communicate with people. And, and the only way you communicate with people is through the use of that data. So I think if there can be informal discussions around the use of data, so that does help, rather than being a culture of being scared, so use data that you ended up not using it at all”* (Source: L).

4.4.5. Culture

The fourth key category of organisational design is *culture*. This category encapsulates the participants' perspectives in terms of *openness to change, power dynamics, analytical culture, and beliefs.*

Organisational culture is concerned with the assumptions and behaviours of an organisation's members that are taken for granted. It helps organisational members to respond to issues in a particular way and help them make sense of the organisational context within which they work (G. Johnson, 2019). According to Laudon and Laudon (2020), information management involves various factors, among which organisational culture plays a key role. In addition, organisational culture is deemed as an influential factor in facing new data and information when making decisions and changes. This is because changing decision-making processes would change power structures, peoples' roles and the way organisational members communicate (Frisk and Bannister, 2017). In total, the culture of an organisation is an important factor in the implementation of big data analytics and its success (Zhu et al., 2021). Furthermore, a well-synchronised culture helps enhance the sense of belonging and sustainability of the organisation (Upadhyay and Kumar, 2020).

4.4.5.1. Analytical Culture

Many of the participants have identified organisational culture as one of the important aspects of organisational design. According to the findings, the following passage shows that when big data analytics was first introduced and applied, people did not trust the data and insights emerging from it. This concept refers to an analytical culture which has repeatedly been mentioned by participants as an important factor in implementing big data analytics and reaping value from it.

> *"When I first joined this business, people didn't really trust it. It was definitely something that was unknown. It was a huge buzzword in the community, but it didn't seem tangible to a business. You see lots of things about big data and massive steps forward within research and academia. And you get these huge businesses that are goliaths in the market and they are able to use it. But it*

definitely seemed when I first joined a very alien concept to a businesses' culture." (Source: A).

According to the findings, some people are reliant on data and others, on the other hand, regardless of access to data, are not willing to consider the change and be more reliant on data. This aspect of organisational culture has been identified by the participants as *openness* to change and embracing the changes and innovation that data might bring. In the following excerpt, the participant explains that this is not because of the lack of capability but might be because of willingness to embrace the change.

> *"So data is recognised as being extremely important. But on the other side, there are people who are not really engaged with data just as such. And there are various reasons for that, it's not that they do not have the capability, or something might be that they're very focused on the operational aspects. Right. And as a result, they do not necessarily have the time to step back. And then think about, okay, I have done all of this, I have generated so much data, what can I do that could do with that data? You know, how can I improve my own activities based on the data? It's not something that everybody considers. So, I think, yes, there are some people who are extremely reliant on data and because they understand its importance, but equally, you will find other people who are not engaged with data at all."* (Source: E).

The findings show that one of the aspects of organisational culture is *power dynamics* identified by the participants. Participants have regularly argued the various changes, advantages and disadvantages that big data might bring about. One of the changes that might take place in the presence of a deluge of data and skilled data analysts is the change in power dynamics. As evidenced in the following excerpt, people who have access to crucial data, analyse it and provide support for the senior management team (key decision makers) can influence the decisions through the information they provide. Therefore, key data individuals such as data analysts and scientists have more power than before as the role of data in running businesses is increasing.

> *"I think the one thing that data allows organisations to do is to challenge the existing structures. Because if we assume that knowledge is power, as we were saying earlier, so you have access to data. And you have the capability to convert the data into information into knowledge into wisdom, and act upon that. And those people are suddenly very powerful. Right. And those people within any organisation may not be the senior managers. So, the people who actually have access to the data, they actually have more power, because they can choose to share what they want to share, and choose not to share what they do not want to share."* (Source: E).

In response to the question about power dynamics, data analysts have emphasised that they wish they had more power in terms of decision-making authority. In the following passage, a data analyst, after highlighting that data analysts need more decision-making power, argues that this does not eliminate the need for collaboration and productive dialogue between individuals.

> *"I think definitely they need to, but I do think again, collaborate on a bit more than just being like, what else is my thoughts. Okay, yeah, don't use the words What up? Here's my thoughts."* (Source: H).

Another participant similarly highlights the role of data analysts in decision-making processes, arguing that they should be more involved on both sides of the fence.

> *"I personally feel data analytics person needs to very much be on the side of a decision-making team. I would say they should be definitely be consulted and input strongly taken on both involved in those decisions."* (Source: M).

4.5. Chapter summary

This chapter aimed to present the findings of the study in light of the research question. In doing so, three main themes of the study including decision-making, dynamic capabilities, and organisational design, and their associated subcategories and open codes that emerged from the data, were presented. The findings within the chapter represent the perspectives of the participants on various aspects of the phenomenon under investigation. Chapter five discusses the results of the study in relation to the literature review and also presents the empirical model developed in this study.

5. Chapter five: Discussion

5.1. Introduction

As mentioned earlier, the primary purpose of this study is to enhance understanding of the impacts of big data on organisational design, particularly decision-making in dynamic environments. Particularly, how organisations can better address big data environments by redesigning their organisations or developing new capabilities. The purpose of this chapter is to provide a comprehensive analysis of the study's key findings, which have been presented in the previous chapter and are related to the existing literature, research question, aims and objectives. It also aims to highlight the various areas of literature that can be expanded or enriched through the study's findings.

The first goal of this chapter is to find ways to strengthen the key findings by taking advantage of the existing literature. This approach helps to position the study's findings in a more prominent position by reviewing and discussing how other scholars have discussed the emerging concepts. In addition, the chapter aims to comprehensively analyse the key findings by linking the study to the broader theoretical and practice landscape.

Another goal of this chapter is to underline the importance of the key findings in order to expand the existing literature. This could be achieved by identifying the areas of the current literature that are important to the development of new knowledge and are in agreement with the findings of this study and also by identifying areas that might not be in agreement with the results of this study. This approach can also lead to interesting discussions about the various issues that require further research and analysis.

Therefore, the researcher would be able to provide an accurate and appropriate answer to the research question with an understanding of the concepts and pinpointing the relationships between them. This chapter discusses the key findings of the study (including the main themes of decision-making, dynamic capabilities, and organisational design) and their relation to the existing literature. This ultimately results in a better understanding of the conceptual model introduced earlier and the development of a new framework to address the research question.

5.2. Discussion of the theme of decision-making

This section discusses the findings about the theme of decision-making that emerged from the data. This core category (theme) is concerned with the various features of decision-making processes and their evolution in organisations identified by the participants.

Key findings about a number of subcategories associated with decision-making range from decision-making styles, including normative decision-making, intuitive decision-making, and natural decision-making, to decision-making processes such as team-processes are presented in this section.

5.2.1. Normative decision-making

Normative decision-making was found to be one of the most significant dimensions of decision-making in big data environments. Many of the participants highlighted the importance of this style in decision-making processes. For example, participants repeatedly mentioned how logic and evidence would guide them in decision-making. The normative decision-making style tends to be used more in the operations of organisations that heavily rely on the insights coming from big data. For example, some of the main operational decisions are made automatically using mathematical algorithms and artificial intelligence, where data is fed into the machines and decisions are made automatically. This is particularly important in real-time processes where real-time decisions are extremely important. Participants argued that they take advantage of automated decisions for their operational decision-making processes, and they believe it could be more valuable for their firms if they could make other decisions as fast as possible too. It is important to note that automated decisions are mostly taken by utilising structured data.

Participants believe that data analysis is a vital part of any organisation's operations, as it can help support various decisions, from daily and short-term goals to long-term decisions such as strategic ones. It can also help in identifying areas of potential improvement and developing a strategy for the long term. These data analysis tools are regarded as an essential part of businesses working with big data. In this sense, the findings show that data analysis plays a key role in supporting normative decisions.

The participants have frequently brought up real-time or near-time analysis of the data. Evidence shows that failure to provide the correct information for decision-makers in a timely manner may affect the business. Key factors in doing so are the ability of data analysts to provide the timely insights needed for the decisions. It is important to note that the exponential increase in the data and information and related tools for data analysis available to managers makes information processing easier and faster than before. Therefore, the interest in this specific style of information processing is increasing (Bullini Orlandi and Pierce, 2019). Findings are in agreement with the study of Bullini Orlandi and Pierce (2019), who argue that because of the nature of location-sensitive and real-time data coming from customers, an analytical decision-making style would be more useful in this setting. Plus, participants discussed there are other capabilities involved in facilitating this process, such as the technological aspects and cultural dimensions that are discussed in the following sections and all are linked in the final section of the discussion chapter.

Another dimension of the normative decision-making style identified by participants is the evaluation of information. This evaluation of information could be conducted by machines and AI for automated decisions; it could be conducted by the data analysts supporting the decisions or merely by the final decision makers. If the evaluation of the information is adequate, the process of decision-making might be normative; however, this is not always the case, and decision-makers might resort to other styles where the information does not yield adequate insights. The findings show that evaluating information is a challenge many businesses can face. This concept is about assessing the information in a suitable way (not only analysing the data), in other words, in a way that can be useful for a particular decision.

Thus far, according to the findings, the normative decision-making style seems to be an appropriate approach toward decision-making in big data environments as this style relies on logic and evidence from data. This is in line with what Dane and Pratt (2007) believe as normative (rational) decision-making draws upon reason and evidence, and its consequences are known earlier because courses of action depend upon data analysis and evaluation of information directly relevant to the matter. However, according to some of the factors identified by participants, adequate information is not always available for rational decision-making purposes. This could be because of time pressure, lack of sufficient and accurate data to interrogate, or the decision makers' individual styles. Therefore, when decisions are taken automatically by machines, they merely rely on data and evidence, but other decision-making styles might be used when individuals take them. Some of the ways to enhance this decision-making style, such as developing dynamic capabilities and redesigning the organisation, are discussed in the following sections.

Accordingly to Simon (1987:63), “The effective manager does not have the luxury of choosing between ‘analytic’ and ‘intuitive’ approaches to problems”. In addition, Nyström (1974) believes normative and descriptive approaches complement each other rather than competing in uncertain conditions. Nyström (1974) also highlights the role of information in reducing uncertainty which is in line with the findings of this study; however, the provided information is not necessarily suitable and relevant to the subject matter, so it might increase the uncertainty. Therefore, the study’s results show that there is always room for enhancing the quality of the information provided for the decisions and improving the quality of decisions.

5.2.2. Intuitive decision-making

Intuitive decision-making style was found to be one of the dimensions of decision-making in big data environments. In this model, intuition and experience play an important role rather than evidence (Oliveira, 2007; Holzinger, 2014). According to the findings, participants have identified *intuitive cognitive style* as one of the aspects of the intuitive decision-making style. They believe that decision-makers might resort to their intuition if they do not understand the data, there is an element of time pressure, or they cannot trust data for their decision-making process. This is linked to the previous section, as a lack of adequate information for decisions might result in intuitive choices.

In big data environments, the literature review argues that this style may not be the best approach to be taken. Dane and Pratt (2007) argue that heuristic decision-making models might affect the effective evaluation of problems and courses of action established to address those issues. Those decisions might be taken at the individual level but the consequences scale up to the organisational level as Nyström (1974) also argues that different cognitive styles of decision-making (analytical versus intuitive) at the individual level would affect the organisational level decision-making concerning information collecting and processing because those cognitive approaches would guide the type of information being sought and processed. Participants highlight that decision-makers sometimes rely on their *heuristics* for making decisions. In this decision-making process, they usually rely on their mental shortcuts, which are built over time based on experience, learning, and performing various tasks. Therefore, if this becomes a habit, that will affect future decisions as well.

Again, decision-makers perceive problems in different ways according to their mental models, reasoning techniques, experience, feelings and how much they trust the data. Then, if the insights from the data are not in line with their perception of the problem, this would result in intuitive decision-making. This is also influenced by other factors such as organisational design and culture, which are discussed and linked to these discussions in the following sections.

5.2.3. Natural decision-making

Natural decision-making is the third key category of decision-making theme that participants identified. In reality, they believe, it seems that most of the decision-makers assimilate the concepts of normative and intuitive approaches at the same time rather than sticking to one specific approach. The reasons mentioned earlier such as the perception of the decision-makers are among the influential factors. Participants mentioned that some people are more familiar with some parts of data and they trust that bit, and on the other hand, when they do not understand the data, they cannot trust it. Therefore their decisions will not be purely normative (Burstein and Holsapple, 2008). This is mainly because data comes from various sources and can take multiple formats, which is not necessarily easy to interpret (G. Klein, 2008).

Additionally, this would result in an abundance of data and information, which increases the complexity of the situation at hand; therefore, decision-makers would assimilate both normative and intuitive styles to make decisions. This is in line with the study of

Bullini Orlandi and Pierce (2019) which conducted a study on reframing the decision-making styles in technological settings by comparing analytical and intuitive information processing styles. They found out that because of the nature of location-sensitive and real-time customer data, an analytical decision-making style would be more useful in this setting. However, their results support the idea of naturalistic decision-making as a combination of either of those mentioned processes simultaneously, resulting in more effective decision-making.

5.2.4. Team processes

The fourth key category of decision-making is *team processes*. This category encapsulates the participants' perspectives in terms of *information flow and processing capacity, responsibility, synergy and collaboration, diversity of skills and expertise, conflict of interests, and time pressure.*

Regarding team processes, participants have highlighted that team processes tend to be democratic, but it is very important within an organisation that somebody is accountable for the decisions they make, as the decisions will have consequences. That person also tends to be the team leader or the team manager; however, they usually make sure that others contribute to the decisions. Participants particularly mentioned that strategic decisions are highly important in terms of accountability as they are more long-term and have more profound effects on businesses.

Results show that decisions that are made within teams can benefit from the diversity of skills as the diversity of thoughts, ideas, expertise, and personalities could contribute to better decisions by challenging various ideas and bringing a wider variety of thoughts to the table. These findings are in line with the study of Berry (2006) as he argues teams are more effective with respect to decision qualities as they are able to process a greater amount of information and they are made up of diverse expertise, creating a synergetic effect by criticising and amplifying each other’s ideas (Boulesnane and Bouzidi, 2013). However, he argues that there might be some drawbacks to team processes as they are considered time-consuming as members have to have face-to-face meetings or other drawbacks such as minority domination and social pressures.

In big data environments, in particular, data analysts play a crucial role as a supporting function in decision-making processes by providing the necessary information for the decision team. Participants believe that the participation of data analysts, who are well aware of the insights that emerged from the data, within decision-making teams could contribute to enhancing the dynamism of decisions. Particularly, when time pressure is involved, team processes could improve the timeliness of the decisions.

Information flow as another important factor that can facilitate or hinder team decision-making processes, was also identified by the participants. In this sense, they referred to trust and openness as key factors in sharing information within teams , which will result in improving information flow and knowledge management (Mckenzie et al., 2011), consequently, better and faster decisions. Similarly, participants repeatedly highlighted the key role of the collaborative (Abubakar et al., 2017) decision-making style, even in strategic decisions, which yields more effective results. According to the findings, some organisations involve their data analysts in their decision-making teams actually to discuss the insights and intelligence extracted from data.

According to Eisenhardt (1999), effective strategic decision-making involves identifying and monitoring opportunities and threats in a timely manner. Having a well-defined collective intuition is also important to enhance the effectiveness of the process. Developing effective teams and provoking ideas that cause conflicts of thought can help improve the decision-making process. Besides being able to identify and monitor the opportunities, having fun and being able to agree on the goals can also help defuse the tensions during the process. However, Steptoe-Warren et al. (2011) believe instead of focusing on building a long-term position, strategic decision-making should consider the continuous improvement and adaptation of the organisation. They stated that this approach is more about developing a strategy that is adaptable and improving. They also emphasise the importance of external factors in making strategic decisions. This is because, in addition to identifying and monitoring the opportunities, having a well-defined strategy can help determine if the choices are operational. It is worth noting that organisational culture plays an important role in facilitating information flow within teams, which is discussed in the following sections.

However, some participants argued that data analysts within their organisations are not involved in decision-making processes. This has important implications for organisational decision-making processes and design, as the communication of insights would be more effective if the data officers and analysts were involved in evidence-based decisions. This is because, according to the findings, where senior managers deal with familiar markets and data, processing the data will be much easier. However, because of facing the deluge of new data coming from brand new markets, processing the data individually might be challenging. So this would call for collaboration and team processes, particularly for data analysts who are more familiar with the data. According to Fredrickson (1986) centralisation might contribute to strong coordination of decisions but obviously would tax decision makers' cognitive capacities at higher levels. That is why team processes might be able to mitigate that issue.

This study's findings align with the study of Huber (2003) in terms of the future of business environments and decision-making processes. He believes that two main approaches could be considered to cope with multidimensional decision situations created by environmental complexity. First is enhancing the knowledge and mental models of individuals who make decisions (this also refers to dynamic managerial capabilities which is discussed in the following section) through various processes such as training. The second approach is concerned with learning and possession of knowledge of various kinds in case of facing more complex issues. This implies that broader decisions would help decision units to learn, and consequently, more individuals would be involved in decision-making processes. As the first approach highlighted, knowledge and mental models of decision-makers would be influential factors. In the same vein, Mckenzie et al. (2011) bring up the critical role of knowledge management, which is subject to individual and organisational learning capacity, in developing fast decision-making processes. In addition, through collaboration with partners, organisations can improve their access to knowledge by filling in the knowledge gaps and providing relevant and cost-effective advice. Similarly, the three organisational capabilities in facilitating decision-making are intelligence collective, knowledge management, and knowledge acquisition. Intelligence collection is a process involving individuals' collaboration to solve problems and create synergy. The second is knowledge management, which is a process that involves the collection, storage, and dissemination of knowledge. And the last is innovation which is the exploitation of ideas resulting in organisational productivity and growth (Boulesnane and Bouzidi, 2013).

Figure 5-1 illustrates the theme of decision-making that emerged from the data. The central gear represents the decision-making in organisations in the big data environment. The surrounding gears show the various decision-making styles in this particular environment. Please note that gears have been selected to show that decision-making processes evolve, plus decision-making activity is a continuous activity within organisations. As shown, all four various styles contribute to the main decision activity. However, their effectiveness has been shown by the size of the gears (the bigger the outer gear, the more effective the style is in data-intensive environments).

Figure 5-1: Decision making (Source: author)

5.3. Discussion of the theme of dynamic capabilities

This section discusses the findings about the theme of dynamic capabilities that emerged from the data. This core category (theme) is concerned with the various features and dimensions of *dynamic capabilities* within the studied organisations identified by the participants.

Key findings about a number of subcategories associated with dynamic capabilities, range from *managerial capabilities*, *knowledge management, and learning to environmental dynamism,* are presented in this section.

5.3.1. Managerial capabilities

Managerial capabilities were found to be one of the main aspects of dynamic capabilities encapsulating the participants' perspectives in terms of *leadership, awareness, cognition, human capital, and social capital.* This is mainly because managers as key decision makers play an important role in taking individual-level decisions (or by contributing to organisational decisions), which will eventually scale up to the organisational level, impacting the direction of the business, and defining and designing the competitive position of the firms. This is in line with the study of Kor and Mesko (2013).

Several key aspects of managerial capabilities (Ferraris et al., 2018) have been highlighted by the participants, such as leadership. In this sense, they argued that managers play a significant role in promoting the importance of evidence-based decisions, trust in data, and creating an analytical culture within organisations (Frisk and Bannister, 2017; Thirathon et al., 2017; Upadhyay and Kumar, 2020). As a result, this positive attitude toward evidence-based decisions could lead to trust in data and change the decision-making styles from more intuitive to more evidence-based decision-making style, which seems to be more useful in big data environments (Zhu et al., 2021). Participants believed that this would not be possible without the support of the senior management team. In addition, as emphasised by the participants, this would increase individual awareness of the data, its benefits, and even its disadvantages.

This study's findings suggest that a deep understanding of the data collected and analysed by an organisation can help it reap the most value from its data which is in agreement with the literature of big data (Hilbert, 2016). The participants state that having a good understanding of the data can help improve the efficiency of an organisation in terms of the communication of the data across various departments and organisations. This is also closely linked to the discussions in the previous section, as having a deep understanding of the data itself would help managers to trust it and make better-informed decisions (Day and Schoemaker, 2016), where otherwise, they might merely ignore the data as they do not understand it. In addition, as discussed earlier, this could be mitigated by team processes and through having data analysts within the decision units who could interpret and communicate the insights that emerged from the data. Furthermore, the findings show that the awareness is not limited to the data but also includes the awareness of the business and its environment. This is because a deep understanding of the business and organisation would result in understanding the needs of the business in terms of data. This would lead to better resource configuration and data collection. This refers to *human capital* as one of the managerial capabilities identified by the participants. There is a relationship between the managers' perception and understanding of the data, with the quality of the data they collect. In other words, a deep understanding and knowledge of the data and its capabilities in conjunction with the data required for the current business could contribute to opening new doors for new customers.

In addition to human capital, social capital was also highlighted by the participant as *social capital* within a team which is concerned with social relations, interactions and networking within a team. This facilitates the flow of information and enhances the decision-making process.

Participants have regularly identified the role of *cognition* in managerial capabilities. Findings show individuals' capabilities in assessing the effectiveness of various decisions and metrics might be different depending on their cognition. This is because perceptions, skills, thought processes, experiences and knowledge acquisition techniques vary, resulting in various cognitive capacities. One of the factors in shaping cognition is experience, as the findings show that experience and learning from past experiences would shape and influence cognition and, consequently, future decisions. Therefore, it seems that managerial judgement plays an important role in the success of dynamic capabilities; this is in line with the study of Day and Schoemaker (2016:75) as they state: "Even the best-designed dynamic capabilities, however, cannot succeed without seasoned managerial judgement.".

The findings of the study in terms of managerial capabilities are in agreement with the study of Ander and Helfat (2003), where they categorise dynamic managerial capabilities into three concepts: managerial human capital, social capital and cognition. They argue that managerial interactions with various networks build their personal and professional experience, forming managerial cognition. It is also important to note that those elements are interconnected and all are necessary for the success of dynamic managerial capabilities. Consequently, managerial understanding helps managers make better decisions in a deluge of information. However, as Kor and Mesko (2013) argue managerial interactions should not be limited to interactions within the organisation, and those interactions could be outside the organisation too.

Similarly, McKenzie et al. (2011) developed a set of principles that help improve the dynamic decision-making process. These include human capital, relational capital, and structural capital. Human capital is focused on developing and retaining experts, while structural capital is on the use of technology to enhance the knowledge base. Relational capital is associated with internal and external collaboration, which requires an integrated approach. Finally, managerial cognition is the ability to make decisions based on the beliefs and mental models that are influenced by experience. Additionally, individuals abilities that result from the interaction between their life experiences and innate abilities influence strategic decision-making by impacting resource configuration and orchestration (Beck and Wiersema, 2013). Kunc and Morecroft (2010) argue that managers' mental models and cognitive capacities based on various knowledge and experience would influence the way they perceive the industry and environmental changes and, eventually, resource allocation.

5.3.2. Knowledge management

Knowledge management was found to be one of the main aspects of dynamic capabilities encapsulating the participants' perspectives in terms of *articulation, constructive collaboration, tacit knowledge, explicit knowledge, exploration, codification and knowledge exchange.* Due to the availability of IT tools and a growing number of knowledgeable individuals in the organisation, it has become easier for businesses to manage their information. One of the most critical factors that businesses consider when it comes to learning is knowledge (Hislop et al., 2018). Over the last 30 years, a shift has occurred from mere production to learning about the process, people and behaviour (Harlow, 2018).

There are various ways in which knowledge is shared between members of an organisation. Knowledge articulation was among the important aspects of knowledge management identified by participants. They repeatedly mentioned the concept of knowledge articulation and the mechanisms by which it occurs such as formal communication channels. However, they highlighted the role of conversation in enhancing knowledge articulation. This would clarify what sort of knowledge needs to be sought and shared between decision-makers and data analysts. This is also particularly important in big data environments as managers and data analysts are facing a deluge of information, increasing the complexity of the contexts within which decisions are taken. However, compared to explicit knowledge which is easily transferrable and represents different ideas, tacit knowledge can be interpreted in various ways and is not easily transferrable (Harlow, 2018). This is particularly important in big data environments, as data analysts might share and communicate their implicit knowledge about the data, making it challenging to transfer the insights accurately.

The findings show that constructive collaboration is a concept that refers to the ability of organisations to share collective knowledge. It allows participants to improve their knowledge and share their experiences with others. According to participants, this type of collaboration can help them keep up with the changes in the world around them. This highlights the importance of up-to-date knowledge in big data environments. This is because, in moderately dynamic environments, DCs are detailed and analytic processes relying heavily on existing knowledge, whereas in highly dynamic environments, they are unstable processes and experiential ones relying on the quick creation of new knowledge. Immediate creation of new knowledge to address highly dynamic environments requires learning mechanisms which is also repeatedly emphasised by participants. This is also in line with the study of Eisenhardt and Martin (2000), discussing that the evolution of dynamic capabilities is guided by learning mechanisms meaning that they are path-dependent. Learning will be discussed in the following section.

Findings show that exploring knowledge is one of the key concepts identified by participants with regard to knowledge management. According to the findings, participants have repeatedly mentioned the aspect of knowledge seeking (exploration). As mentioned earlier, one of the reasons for seeking is addressing the dynamic environments. Another reason was to improve and optimise the current processes and build on their extant knowledge. When the environment is moderately dynamic, decision-makers can rely on past knowledge and generalisation but big data environments call for the rapid creation of new knowledge. This is in line with the study of Eisenhardt and Martin (2000). Once the new knowledge is sought and explored, it should be acted upon. It is important to note that there is no conflict between the exploration and exploitation of new knowledge as Curado (2006) argues the combination of both exploration and exploitation is not conflicting and would result in synergy and reinforce each other's effects, although it is difficult to implement.

Knowledge management is one of the important factors in developing dynamic capabilities. The findings of this study are in line with the findings of Ferraris et al. (2018) as they believe companies with the ability to manage various types of knowledge by means of integrating extant and new knowledge, might be able to leverage the organisational capabilities (such as big data capabilities) more effectively. As mentioned earlier in the literature review, there is an overlap between dynamic capabilities and knowledge management, which is underpinned by learning. Learning is another important factor in dynamic capabilities which is discussed in the following section.

The findings of this study suggest that developing effective knowledge management capabilities is very important for both managers and data analysts. According to the findings, there are various ways by which knowledge is shared within companies in big data environments, such as formal communications channels and informal communication channels such as conversations between organisational members. This knowledge exchange will result in enhancing the awareness of people involved in decision-making processes and operations. The findings reveal that data management has massively improved due to migrating to an integrated system that facilitates data analysis and sharing of information. In this case, data, information, and the results of the analysis could be accessed across the organisation by using dashboards.

However, in terms of communicating insights that emerged from big data, the study revealed that focusing on only the small fragments of data would not provide them with the necessary insight to make informed decisions. Instead, managers and data analysts should consider the overall summary of the data to ensure that they can identify key insights. This is why it is important that the data analyst takes a bottom-up approach when it comes to knowledge management.

"In case an organization is capable of implementing proper systems and developing the right capabilities, the true potential of big data availability may then emerge" (Rialti et al., 2019:2). The importance of developing dynamic capabilities has been highlighted in the literature and this study's findings. Accordingly, Wamba et al. (2017) consider big data analytics capability as a dynamic capability to achieve a sustainable competitive advantage, which is increasingly evolving into a vital aspect of decision-making in many businesses. In addition, information extracted from data is deemed as one of the most significant organisational resources (S. F. Wamba et al., 2017). Additionally, to enhance the effectiveness and quality of decisions and decrease the level of uncertainty, an organisational change regarding structure, processes and mechanisms seems to be necessary alongside business analytics, which is subject to information flow (Kowalczyk and Buxmann, 2014a). This emphasises the significant role of knowledge management, information and dynamic capabilities.

One critical concept in developing dynamic capabilities is the manipulation of knowledge resources (Eisenhardt and Martin, 2000). Accordingly, an empirical study by Ferraris et al. (2018) revealed that a certain amount of knowledge management and big data analytics capabilities are required to reap value from big data. Key assumptions in knowledge management literature include knowledge becoming a critical asset due to various factors. These include a huge amount of social and economic transformations, the changing nature of the work and the increasing importance of intellectual work, and practical knowledge management that can be a source of competitive advantage (Hislop et al., 2018). According to KM literature, some of the other influential factors in KM include organisational culture, leadership, organisational interest in learning, knowledge management processes, organisational structure and technological infrastructure (Curado, 2006).

5.3.3. Learning

The third key category of dynamic capabilities was found to be *learning*. This category encapsulates the participants' perspectives in terms of *experience, reflection, interactions, training, and dialogue*. Learning has been mentioned repeatedly by participants as an enabler of dynamic capabilities which is an important part of knowledge management as well.

There are various ways by which organisations and their members can learn (Doloriert et al., 2017). The findings revealed that one of the key methods of learning for big data environments is through training. This is particularly important for data analysts as they might require new skills to deal with a deluge of information coming from various sources. Therefore, in terms of training, their knowledge needs to be up to date as the conventional methods are insufficient to address big data. The findings show that training is not limited to data analysts, other members of the organisation and whoever deals with data, their insights, and is involved in decision-making processes need a certain amount of awareness about the data. Additionally, as the decisions and their consequences are linked to the business, understanding the data itself is not enough without a good understanding of the business processes, operations and their needs.

Interactions with others within and outside organisations perhaps are among the most important aspects of learning, as revealed by the results. The findings show that, apart from the technical aspects of the analysis which is of high importance, interactions with other teams and members would be helpful in terms of learning new skills and also how to communicate the insights gained from data to decision-makers. Formal learning mechanisms such as training, which was mentioned before, would enhance the technical knowledge of the concepts, but interactions with others will also result in consolidating the extant knowledge and learning more tacit knowledge from others.

These findings are consistent with the study of Curado (2006), who argues that the learning process is not only individual but also a social phenomenon meaning that learning would be achieved through interactions among people and coordination. Therefore, learning is a dynamic process (Mohamud and Sarpong, 2016) requiring time to happen and would happen at different levels of individual, group and organisation. He explained that there are two types of mechanisms that people can use to acquire knowledge: internal and external. The former involves performing various tasks and interactions inside the organisation, while the latter involves acquiring knowledge from outside sources. Reflection is another dimension of learning found in this study. Reflection is key with regard to resource allocation and looking at how those strategies were effective in the past and learning from them.

The findings are consistent with the study of Zollo and Winter (2002) where they categorise learning mechanisms into three groups including organisational routines and experience accumulation, Knowledge articulation and Knowledge codification. They deem learning mechanisms focal to the analysis of dynamic capabilities. For the first mechanism, they particularly argue that they require a continuous update in unpredictable environments. For the second mechanism, without the participation of members in collective discussions, learning would not be possible. This is because collective competence can be attained through the exchange of knowledge. This can be achieved through the use of knowledge articulation, which can help members improve their awareness of existing routines. And for the last mechanism, the literature has accentuated that codification would facilitate knowledge diffusion, and it is a significant element in the capability-building picture (Zollo and Winter, 2002; Curado, 2006). Additionally, tacit knowledge and codified knowledge are considered as drivers of dynamic capabilities (Hidalgo-Peñate et al., 2019). The findings of this study are also in line with the study of Mohamud and Sarpong (2016) who argue that learning can be considered as an origin and the key ingredient of dynamic capabilities which requires a continuous update. A continuous update is key in highly dynamic environments as also mentioned earlier, those sorts of environments call for rapid creation and exploitation of knowledge. It is important to note that organisational culture plays a key role in facilitating learning mechanisms, which is discussed in the following sections.

Dialogue was found to be a significant learning and knowledge-sharing mechanism in this study. A constructive dialogue can be extremely important in generating new ideas, sharing thoughts, and learning from other members of the organisation in a short period of time in comparison with other learning methods discussed in this chapter. This usually occurs in informal conversations, for example, during a coffee break between organisational actors. In this particular context, actors freely share their ideas and they are open to ideas in comparison to formal discussions within decision teams. This would help personnel to communicate in a faster and easier way, and share ideas and thoughts, and learn from them.

“organisational learning is the acquisition of new knowledge by actors who are able and willing to apply that knowledge in making decisions or influencing others in the organization” (Miller, 1996:486). This statement from Miller brings to the fore the importance of the ability and willingness of individuals within organisations to facilitate learning. This study has highlighted some of the ways in which ability can be improved, as well as the mechanisms for enhancing the willingness by means of organisational culture and leadership.

5.3.4. Environmental dynamism

The fourth key category of dynamic capabilities is e*nvironmental dynamism*. This category encapsulates the participants’ perspectives in terms of *regulations, industry and competition, and a deluge of information.* The findings show that there are various factors involved in making a big data environment highly dynamic. Regulations was found to be one of the main reasons. Once GDPR (General Data Protection Regulations) was enforced in May 2018, it had important implications in terms of handling data for organisations. Participants identified that the way they collect data, analyse it, and share it has been influenced significantly to make sure they comply with the regulations and share it with the right people.

Regulation is not the only factor that has contributed to environmental dynamism. There are other factors such as changes in the industry in terms of policies, that need to be monitored constantly and acted upon. The covid-19 pandemic was another factor at the time of conducting this study that massively impacted organisations and their operations.

The findings reveal that data is increasingly becoming an important part of many businesses. Competitors of companies and how they describe themselves alert other competitors that they need to be aware of the contemporary changes in the industry to keep pace with those waves. The data industry is one of the industries that has witnessed a lot of changes and waves. Results show that this is mainly because the power of data and analytics is increasing and can influence the competition in the market. In addition, big data analytics capability is a dynamic capability where data and analytics can be a source of competitive advantage.

Figure 5-2 summarises the discussions around dynamic capabilities within data-intensive environments found in this study. All four main elements of dynamic capabilities are linked together and are not independent. Various factors cause environmental dynamism; this study focuses on data-intensive environments as a context. As discussed earlier in this chapter, managerial judgements are key to the success of dynamic capabilities in big data environments. *Leadership, awareness, cognition, human capital, and social capital* are among the dimensions of managerial capabilities. Knowledge management is another dynamic capability suggested by this study in data-intensive environments that need to be either developed or improved, as big data contributes to creating huge amounts of knowledge that need to be managed. This knowledge needs to be created and shared within the organisation. As suggested by this study, there are various mechanisms by which learning can be improved in data-intensive environments. However, as shown in the diagram, informal dialogue is at the heart of learning. Particularly, this dialogue is key between organisational members, especially decision-makers, managers and data analysts who communicate the insights gathered from data to their managers.

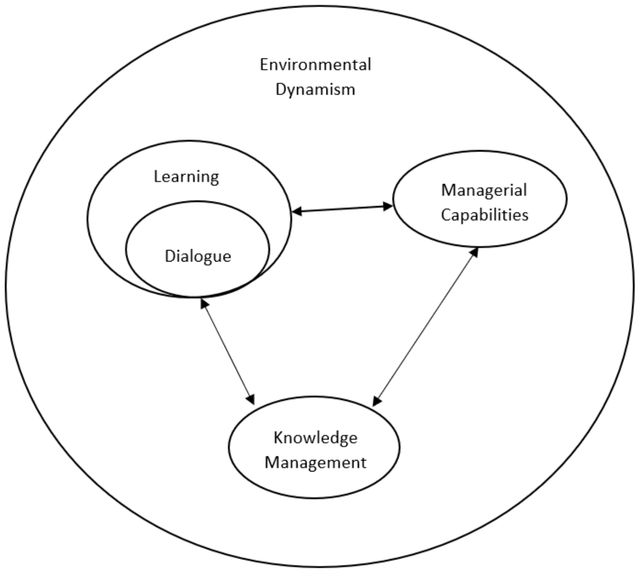

Figure 5-2: Dynamic capabilities (Source: Author)

5.4. Discussion of the theme of Organisational design

This section discusses the findings about the theme of organisational design that emerged from the data. This core category (theme) is concerned with the various features of organisational design and their evolution in organisations identified by the participants.

Key findings about a number of subcategories associated with a number of subcategories related to *organisational design* ranging from *organisational infrastructure, human resources,* and *structure* to *organisational culture,* are discussed in this section*.*

5.4.1. Organisational infrastructure

Organisational infrastructure was found to be one of the key categories of organisational design. This category encapsulates perspectives in terms of *data storage, IT, technological challenges, and data capture.* An information technology infrastructure is a type of shared technology resource that enables a firm to provide necessary information systems. This includes hardware, software, and services that are shared across the organisation. It also enables the firm to manage its internal processes, such as decision-making processes.

The findings show that the organisational infrastructures, mainly IT infrastructures, have played a key role in supporting business strategy and decision-making. IT infrastructures are key to information systems, according to the findings, as various teams might use the same data in a different manner. So it is important to share the insights with various teams based on their needs and requests. This is facilitated by appropriate IT infrastructures in place and coordination between data analysts and other decision units. Big data has influenced the organisational infrastructures in terms of capturing, organising, cleaning, analysing and disseminating information within the organisations. The findings show that the continuous update of those processes is important as the amount of data collected on a regular basis varies in terms of volume, variety, and velocity, which makes it challenging to use the same procedures at all times. Unstructured data accounts for the majority of data collected, making data processing increasingly challenging. For example, organisations that are using customer data and feedback about their applications need to make modifications to their products and services based on the data received from customers. Findings show that companies did not find dealing with structured data challenging, as they are using techniques such as SQL servers, Excel, and statistical tools. However, when there is a qualitative note attached to it, they need other tools and techniques and many of the participants argued that this is not a straightforward process and they were struggling with that.

As data is not necessarily collected automatically via artificial intelligence or other techniques, a team of experts might be needed to acquire data. This has important design implications for organisations as information is a strategic resource for many organisations. They might need to think about assigning a team of experts who are solely responsible for collecting, analysing and disseminating insights to other teams in need of it.

The findings are in line with the literature review in terms of the importance of IT infrastructures in supporting big data analytics capabilities. Accordingly to Mandal (2018) IT capabilities are considered as a backbone of big data analytics, attempting to deploy the basic IT infrastructure to support analytics (IT infrastructures and big data analytics capabilities are not mutually exclusive). Particularly, the effectiveness of BDA is contingent upon IT capabilities. According to IS literature, IT is not considered a source of competitive advantage based on the fact it is not a unique resource and is available to other competitors (Devece et al., 2017). However, its integration in conjunction with other intangible assets might contribute to capabilities resulting in lasting competitive advantage (Devece et al., 2017). IT infrastructures would facilitate organisations' ability to detect, process and communicate information on dynamic markets (improving organisational agility) (Battleson et al., 2016).

5.4.2. Human resources

Human resource management was found to be an important aspect of organisational design in big data environments. Results show that the recruitment of skilled data analysts and data scientists is challenging for organisations. This is because there is a shortage of skilled data analysts and scientists and therefore, they come with a high price. It is important to note that data analysts might be able to provide data analysis and report, but they might not be able to interpret the results. This has important implications for companies who are aiming to take advantage of big data as to recruit the right data scientists and provide the necessary training for them. As mentioned earlier, the data processing might require a team of analysts and consultants rather than a single data analyst. They need to have a good understanding of the business processes and operations to help them with better communication of information.

According to Mishra et al. (2018), HR can help companies gain a competitive advantage by developing a deeper understanding of their employee's skills and knowledge. This can be done through the establishment of effective training programs and the development of new employees. On the other hand, having fewer qualified individuals can prevent them from contributing to the innovation process. One of the most critical factors that organisations consider when it comes to implementing a data management strategy is talent management. This is mainly because as data are getting cheaper, data analysts are becoming more valuable (Shamim et al., 2018). This is why it is important that HR has the necessary skills and capabilities to attract and retain effective talent.

5.4.3. Structure

According to the findings, structure is another aspect of organisational design in big data environments. This category encapsulates a number of perspectives, including *moving capital, organisational communication and information channels, centralisation, formalisation and socialisation.*

The findings of this study suggest that there are various forms of information and communication channels that members of an organisation can use to communicate and share their thoughts and knowledge. These include formal and informal channels. The study acknowledges the importance of dialogue, which highlights this channel's importance in facilitating information flow within an organisation. It also does not mean formal communication channels are disregarded. The study also found that both informal and formal channels can be very effective when it comes to disseminating information and responding quickly to situations. Accordingly, results show that many businesses are still struggling to integrate and communicate the collected data into their decision-making processes.

Various devices and technologies are used within businesses to facilitate communication between organisational members. Findings show that technologies themselves can be relatively straightforward, but the problem mainly arises from the user side as to how they use them to communicate information within businesses. According to this study, information flow and communication is the most important challenge companies are facing in big data environments.

Some businesses might heavily rely on one person’s skills in data analysis for the whole organisation. This is because, due to the high price of skilled analysts. This has important implications in terms of the centralisation of power dynamics toward data analysts. In terms of design, it seems that skilled analysts and scientists are gaining more power within organisations in big data environments. However, as discussed earlier, relying on a person’s skills could bring about challenges as well. This is because constant analysis and interpretation of data are key nowadays. Therefore, the lack of availability of that single person might impact the decision-making processes because of the lack of information needed in time. A solution to this was mentioned earlier in the decision-making section to dedicate a data team for data processing purposes (collecting, analysing, interpreting and disseminating). Another factor that could mitigate this issue would be integrating big data in decision-making processes through artificial intelligence and machine learning to automate some of the decision-making processes within their business.

Resource allocation (moving capital) is another crucial aspect of organisational structure in big data environments, as a certain amount of resources (budget) is required to collect suitable data. Companies should spend a respectable amount of money to gain that data, because unless their budgets are too realistic, they will not get the data they want. It seems that the conversation between data analysts and decision-makers (people responsible for resource allocation) is not necessarily straightforward in terms of persuading them to allocate sufficient resources to collect quality data.

The internal design of the organisations is one of the influential factors in facilitating information flow, which is a key part of decision-making processes (Lewis and Fandt, 1989). Both earlier and recent studies on organisational design and structure accentuate the importance of information flow within an organisation which also supports the findings of this study. Earlier studies, such as those of Lewis and Fandt (1989), highlight the importance of effective information processing and disseminating it to decision-makers. They argue organic designs provide better information flow, less rigid and more adaptable internal systems, and flexibility in dynamic conditions (Lewis and Fandt, 1989). This is particularly important as this study focuses on dynamic environments. Curado (2006) believes that organic designs associated with less centralisation and formalisation might be more appropriate for enhancing organisational learning. Furthermore, Csaszar (2013) highlights that mechanistic designs are more concerned with exploitation compared to organic designs, which facilitate exploration. It is important to note that earlier studies are still relevant. However, as big data is a new phenomenon, factors contributing to contemporary market dynamisms might be slightly different from those of earlier markets. Recent factors are more about technologies such as industry 4.0 technologies. In this sense, conditions of recent markets that experience increasing changes regarding technology, global competition and social demography would require more open forms of structures with porous boundaries (Felin and Powell, 2016).

The findings of this study align with that of Snow et al. (2017) as they argue that actor-oriented organisations, in terms of design, are more effective in dealing with knowledge-intensive environments. Regarding the design, they consider three important elements including “actors”, “Commons”, and “protocols, processes and infrastructures”. Actors could be individuals, teams or even organisations that are underpinned by self-organising and collaboration. Commons refers to resources such as data and knowledge (situation awareness is another influential aspect of Commons), and the Protocols and processes are concerned with actors’ behaviours and strategies. In a nutshell, appropriate awareness of the situation and business processes contributes to better decisions. Foss et al. (2013) also argue decentralisation would help with the exploitation of new knowledge. However, this is not always a straightforward process, and complementary practices to encourage this process might be needed, such as communication channels and incentives. Some of those mechanisms have been proposed by this study, such as the role of analytical culture and facilitating conversations and collaborations, which are discussed in relevant sections.

5.4.4. Organisational culture

Organisational culture was one of the key dimensions of organisational design, encapsulating the participants’ perspectives in terms of *openness to change, power dynamics, analytical culture, and beliefs.*

The findings show that analytical culture (trust in data and insights that emerged from it) plays a crucial role in the success of big data analytics initiatives. Although there is a massive step forward within big data research and many of the big companies are taking advantage of big data, it is alien to some businesses’ cultures. In other words, when big data analytics capabilities are introduced within businesses, people do not tend to trust insights that emerge from data easily. Analytical culture is an important factor in implementing big data analytics and reaping value from it (Frisk and Bannister, 2017; Thirathon et al., 2017; Upadhyay and Kumar, 2020).

Another key factor in organisational culture in big data environments is the willingness to change, which refers to the willingness to change and embrace the changes and innovation that data might bring. In the previous paragraph, it was discussed that some members do not trust the data and insights coming out of it, but in this case, people might have access to data and analysis reports but they are not willing to change and embrace it. Results show that this might be because of a lack of understanding of the importance of data and its value for the business.

One of the changes that might take place in the presence of a deluge of data and skilled data analysts is the change in power dynamics. This was discussed earlier in terms of reliance on one person's skills and expertise to provide the necessary analytical outcomes. However, in addition to that, people who have access to the crucial data, analyse it and support the senior management team (key decision makers) can also influence the decisions through the information they provide. Therefore, this is another factor that might influence power dynamics in big data environments. Suppose a business is heavily reliant on big data analytics and the insights coming out of it. In that case, it seems there is a tendency to shift more power towards people who have access to data, analyse it, and provide information for crucial business decisions. If those decisions are evidence-based, thus the information provided could change the direction of those decisions.

Results show that openness to change, embracing innovation, and new trends could yield better results in big data environments. This is in line with the study by Zollo and Winter (2002), who argue that managers who are open to change practices and their organisations are culturally supportive of those mechanisms would be more likely to obtain returns from learning investments. This is also linked to organisational learning. As discussed earlier, there is a need for constant learning within big data environments and cultural support. When there is cultural support and organisations are more divisionised and diversified, then learning investments could yield more favourable results. "The task of the organizational designer, both in concept and practice, is to design structures that put individuals in contact with their relevant environments and to design processes that facilitate learning, sharing and aggregation of knowledge so that the collective organisation can make well-informed decisions” (Felin and Powell, 2016:81).

Literature supports this study’s findings in terms of the importance of culture in supporting decision-making processes within businesses in big data environments. For example, Frisk and Bannister (2017) argue that changing decision-making culture and design could influence the power structure, people's roles, and how people in organisations communicate and share knowledge and information. In addition, According to various industry surveys and articles, an organisation's culture is one of the biggest impediments to implementing BDA (Zhu et al., 2021). Implementing big data analytics would not be effective as such without the organisation’s cultural support. Upadhyay and Kumar (2020) also believe a well-synchronised culture helps enhance the organisation's sense of belonging and sustainability. Furthermore, Thirathon et al. (2017) consider an analytical culture (organisational members’ attitude towards the usefulness of analytics) as a competitive resource, which would help them to make the most of big data. Supporting advanced analytics and facilitating data sharing would influence the organisational design as decision-makers in evidence-based cultures tend to rely on data for their decisions. It seems that awareness and understanding of the benefits of big data analytics could mitigate this issue and enhance the analytical culture. Plus, leaders and senior management teams play a critical role in promoting this culture and creating analytical culture and trust among employees. This is also in line with the study of Rialti et al. (2019)., where a partial understanding of big data analytics and related processes and infrastructures could enhance the barriers brought about by organisational culture.

Figure 5-3 illustrates the above discussions about the theme of organisational design. As shown, organisational culture has a central role in designing organisations to cope with big data environments. The effectiveness of big data analytics depends on organisational cultural support, which is referred to as analytical culture in this study. The organisational structure holds everything together, which also relies on HR for recruiting and maintaining analytics experts and also the organisational infrastructure to provide the necessary tools for big data analytics capabilities.

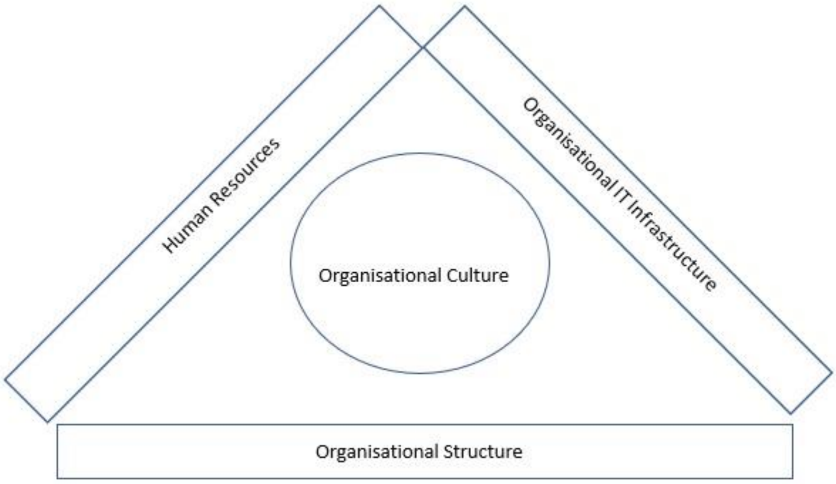

Figure 5-3: Organisational design (Source: Author)

Figure 5-4 illustrates the suggested model of this study. As shown in the diagram data-intensive environment was the context of this study which was created by big data. In the centre of the figure, decision-making mechanism is shown with gears, including various decision-making styles and their effectiveness (the bigger the gears, the more effective the decision-making style) in big data environments. However, the effectiveness of dynamic decision-making depends on various factors in this specific context. At the very centre of the diagram lies analytical culture (shown with a heart sign to emphasise its importance), which acts like an engine or the heart of the system and plays a key role in the effectiveness of other dependent processes. Managerial capabilities, learning and knowledge management, are important dynamic capabilities that need to be developed or reconfigured in order for the organisation to cope with big data environments. In addition, as shown in the diagram, dialogue within the learning circle can be seen as an important learning mechanism. This study identifies various learning mechanisms, however, the dialogue was given significant attention as a meso-level dynamic capability as it facilitates information communication in a faster way. However, those mentioned factors are not mutually exclusive and are interlinked which were discussed in the previous sections in detail. HR's role is highlighted by this study in terms of recruiting and maintaining skilled and talented staff who (in conjunction with existing organisational members) would be able to make sense of big data by using tools offered by IT infrastructures. Last but not least is the organisational structure which plays a significant role in providing a foundation for information flow within organisations.

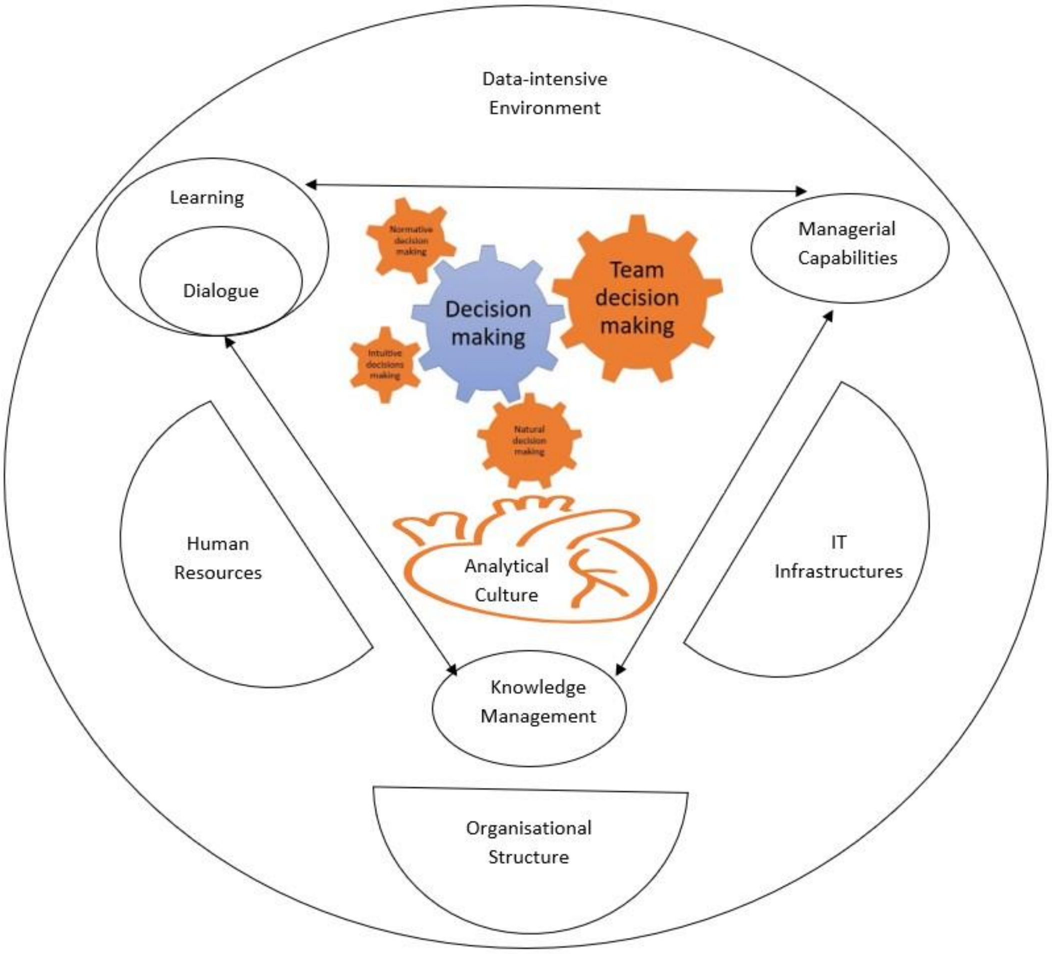

Figure 5-4: Empirical model of decision-making in data-intensive environments (source: Author)

5.5. Chapter Summary

The purpose of this chapter was to provide a comprehensive analysis of the study's key findings which were presented in the previous chapter, that are related to the existing literature, research question, aims and objectives. In doing so, three main themes of the study, including decision-making, dynamic capabilities and organisational design, and their relevant subcategories were discussed in detail. In addition, once each major theme was discussed, a theoretical figure was developed for each theme to further illustrate the discussions. Finally, once the relationship between various concepts was discussed, the main empirical model of the study was shaped and presented. The following chapter is concerned with the conclusion of the study.

6. Chapter six: Conclusion

6.1. Introduction

This chapter aims to bring to the fore summary of the findings of this study and the significance of their contribution. Providing the overview of the study, this section also tries to answer the research questions. Theoretical contributions and practical implications of the study are also presented in this chapter. Before ending the chapter with suggestions for future research, the challenges and limitations of this research are also discussed and included.

6.2. Summary of the findings

The purpose of this stud was to investigate the role of big data in organisations, especially decision-making processes that utilise big data as a source of information, the impact of the organisational design particularly developing dynamic capabilities to cope with the changes brought about by big data, and the reconfigurations in the organisational design. To achieve this goal, the study adopted an embedded and holistic case-study design, where grounded theory informed the collection and data analysis of qualitative data for this study.

Some of the main aspects of the research question were investigated by means of an extensive period of data collection, analysis, engagement and interaction with multiple participants from organisations based in the UK. Key participants included, data analysts, CEOs, data scientists, middle and senior managers, and data consultants (people with a deep understanding of the information processing mechanisms within their companies). The findings were grouped under three main themes, including decision-making, dynamic capabilities and organisational design, which were evident and corroborated by the data collected. It is important to note that these three themes are interrelated and provide a foundation for answering the research questions.

6.3. Addressing the research objectives

To identify the ways in which decision-makers in data-intensive environments are changing their decision-making processes.

Big data has become a mainstream activity within organisations. Its ability to transform the way decisions are made has the potential to greatly affect how organisations approach their operations and decision-making in particular. Due to the complexity of data sources, the need for collaboration between departments and organisations is often required to create a flow of activities using BDA. Due to the complexity of data sources, the need for collaboration between departments and organisations is often required to create a flow of activities using BDA.

Data analysis is vital to any organisation's operations, as it can help support various decisions, from daily and short-term goals to long-term decisions. In this regard, the normative decision-making style seems to be the most appropriate decision-making style in big data environments. On the ground that big data environments call for real-time and fast decisions, some factors could help with improving the time pressure and quality of decisions as follows:

- Take advantage of automated decisions for their operational decision-making processes (using artificial intelligence and machine learning for automated decisions). This could be more valuable for their firms if they could make other decisions as much fast as possible too. This change calls for developing new applications or modifying the new ones constantly to analyse the structured data. This process does not seem straightforward when analysing semi-structured or unstructured data, although there are some techniques to do so such as text mining and voice analysis. This usually requires a human element to assist the decisions.
- New data and information play a crucial role in evidence-based decisions. To make better decisions, quality data is key. The quality of data (reliability, accuracy, completeness, timeliness, consistency, relevance, accessibility, availability) collected and processed is dependent on the type of data and the process involved in its extraction and processing. Big data analytics often requires the participation of various actors from different disciplines to ensure that the data is collected and analysed in a suitable manner. In doing so, collaboration between the data team and decision units is key.
- Change in the decision-making process is not sudden; it takes place over time. This change heavily relies on both technical and cultural aspects of the organisation seeking changes. A certain amount of resource allocation for technological aspects is required. These changes call for constant meetings and

conversations between data analysts and the senior management team to identify the resource orchestration mechanisms. From the cultural aspect, this study suggests that this change would not happen without an analytical culture within the organisation. Senior management seems to play a key role in promoting this trust and culture in data and insights.

- Lack of adequate information and understanding of the data would result in a tendency towards intuitive decisions. In order to mitigate this issue, team decision-making processes seem to be more appropriate, bringing a better understanding of the information available for the decisions. It is important to involve data analysts, who analyse the data and provide insights, in decision-making processes. The findings of this study suggest that this collaboration and clarification of data being analysed would help decision makers, who tend to rely on their heuristics, change over time, build trust in data, and enhance their perception and interpretation abilities.

To identify the factors which decision-makers consider most influential in driving those changes.

There are various factors involved in driving those changes mentioned earlier. **Time pressure** is one of the key factors in driving those changes. One of the changes that were mentioned earlier was shaping team decision units. Results show that the participation of data analysts, who are well aware of the insights that emerged from the data, within decision-making teams could contribute to enhancing the dynamism of decisions. Particularly, when time pressure is involved, team processes could improve the timeliness of the decisions.

In addition, based on the particular characteristics of big data such as 3Vs, real-time and near-time analysis of data is crucial. This would increase the time pressure as well. Although historical data could be useful for predictions, some decisions call for immediate action as the data might lose its value if not acted upon immediately. Again, immediate actions require fact information processing mechanisms. One of those mechanisms which were mentioned earlier was team processes, including people from various backgrounds, including key decision-makers and data analysts.

Enhancing Information flow is another key driver for changes. Information flow plays a critical role in big data environments and decision-making processes. More efficient information flow drives some of the changes in decision-making processes such as formal and informal collaborations and interactions between decision units and other members of the organisation responsible for supporting decisions.

Enhanced Communication is another key driver for the changes mentioned earlier. This not only refers to the communication between members of the decision units but also the communication of data and insights. Findings show that, informal communication and dialogue between members improve data communication significantly. It is important to note that this does not negate the role of formal communications through formal organisational channels such as dashboards.

Market dynamism is another key factor in changing decision-making processes. As discussed in the previous sections, big data environments are particularly dynamic, ranging from changes in industry policies and regulations (such as GDPR) to innovations. Another important factor in making those environments extremely dynamic is the nature of big data, as the data comes from various sources and takes multiple formats which make keeping pace with changes challenging.

To identify how those changes influence organisational design to enhance dynamic decision-making.

Organisational design is influenced by adopting big data technologies. Adopting big data technologies and taking advantage of big data analytics require changes in organisational design as well. Some of the potential changes are discussed here.

Information technology infrastructure is a type of shared technology resource that enables a firm to provide necessary information systems. This includes hardware, software, and services that are shared across the organisation. It also enables the firm to manage its internal processes, such as decision-making processes. On the ground that

IT is the backbone of BDA, therefore it has drawn more attention in terms of resource allocation. It is important to note that organisations tend to migrate to the cloud rather than invest in in-house IT infrastructures that would be costly to maintain and upgrade as the industry is moving fast. This is one of the important changes in terms of enterprise systems and investments. Shifting towards more could-based services and focusing on the core capabilities.

In addition to the investment in infrastructures and services, as data is not necessarily collected automatically via artificial intelligence or other techniques, a team of experts might be needed to acquire data. This has important design implications for organisations as information is a strategic resource for many organisations. They might need to think about assigning a team of experts who are solely responsible for collecting, analysing and disseminating insights to other teams in need of it. This might create new roles or new units or departments within organisations that are responsible for data processing.

Resource orchestration and reconfigurations are also influenced. Results show that the recruitment of skilled data analysts and data scientists is challenging for organisations. This is because there is a shortage of skilled data analysts and scientists and therefore, they come with a high price. Taking advantage of big data requires skilled data analysts and experts that would require attention in terms of recruitment and resource allocation. It is worth noting that recruiting skilled analysts is not necessarily enough in terms of information processing. Results of this research suggest that having an appropriate understanding of the business processes, business model, and communication skills are equally important in communicating information effectively.

Big data has influenced the organisational infrastructures in terms of capturing, organising, cleaning, analysing and disseminating information within the organisations. The findings show that the continuous update of those processes is important as the amount of data collected regularly varies in terms of volume, variety, and velocity, making it challenging to use the same procedures all the time. Monitoring the business processes has become more frequent and dynamic based on the nature of data and information as a significant intangible asset.

Power dynamics tend to change. This has important implications in terms of the centralisation of power dynamics towards data analysts as they are gaining more power due to the critical information they provide for the key decisions within the businesses. In terms of design, it seems that skilled analysts and scientists are gaining more power within organisations in big data environments. However, in terms of structure and decision centralisation, those companies tend to be less centralised and create more decision units and collaborate with analysts and other departments to make faster decisions.

Organisational culture as an important design element, tends to change. Another key factor in organisational culture in big data environments is the willingness to change, which refers to the willingness to change and embrace the changes and innovation that data might bring. In addition, analytical culture and trust in data and its insights is a success factor in big data initiatives. In other words, implementing big data analytics would not be effective as such without the organisation's cultural support.

To develop a framework to enable decision-makers to assess and improve their strategies for adapting to data-intensive environments, including the required capabilities.

Addressing dynamic environments requires dynamic capabilities to help organisations to keep pace with the increasingly changing environments. In doing so, it is important to identify the sources of dynamism within organisations, as we have discussed in this research. Capabilities that need attention are located at various levels of organisations such as personal level, interpersonal level and organisational levels.

Developing dynamic capabilities are key for addressing big data environments and improving dynamic decisions making processes. Managerial capabilities at the personal level play a key role in terms of promoting the significance of evidence-based decision-making, trust in data, and creating an analytical culture within organisations. Leaders, to some extent, are responsible for promoting the analytical culture within their businesses. However, some of the decision-makers may not necessarily trust data and the insights emerged from it that this could be enhanced over time by conversations and collaborations between data people and them.

This study's findings suggest that a deep understanding of the data collected and analysed by an organisation can help it reap the most value from its data. The participants state that having a good understanding of the data can help improve the efficiency of an organisation in terms of the communication of the data across various departments and organisations. This refers to the concept of learning which is a dynamic capability. Learning is increasingly important in big data environments. Learning is not limited to gaining new analytical skills, but also includes learning about the data itself, organisational processes and communication skills. This could be achieved by collaboration between members, especially informal interactions and dialogue which has been highlighted in this study. Creating an informal and friendly environment within which organisational members, particularly people involved in decision units and data analysts, could yield more efficient results in terms of information flow. This refers to the meso level as one of the sources of dynamism within organisations.

There is a relationship between the managers' perception and understanding of the data, with the quality of the data they collect. This could be achieved by involving data analysts within decision units and consulting them rather than merely receiving visualisations and summaries of results via formal channels. Again, informal conversations between key decision-makers and data analysts could be helpful. In addition to human capital, social capital was also highlighted by the study which is concerned with social relations, interactions and networking within a team that facilitates the flow of information, forms managerial cognition and enhances the decision-making process.

In terms of knowledge management, this study highlights the role of conversation in enhancing knowledge articulation. This would clarify what sort of knowledge needs to be sought and shared between decision-makers and data analysts. This is also particularly important in big data environments as managers and data analysts are facing a deluge of information, increasing the complexity of the contexts within which decisions are taken. Constructive collaboration refers to the ability of organisations to share collective knowledge, and allows participants to improve their knowledge and share their experiences with others. This is because, in highly dynamic environments, DCs are unstable processes and experiential relying on the quick creation of new knowledge.

Learning can be considered an origin and key ingredient of dynamic capabilities requiring a continuous update. Continuous update is key in highly dynamic environments; as also mentioned earlier, big data environments call for rapid creation and exploitation of knowledge. There are various ways through which organisations and their members can learn. The findings revealed that, one of the key methods of learning for big data environments is through training. This is particularly important for data analysts as they might require new skills to deal with a deluge of information coming from various sources. Plus, Interactions with others within and outside organisations perhaps are one of the most important aspects of learning. It is important to note that learning would not be effective without the organisation's cultural support. Therefore this supportive culture should be created within the organisation.

A constructive dialogue can be extremely important in generating new ideas, sharing thoughts, and learning from other members of the organisation in a short period of time in comparison with other learning methods discussed in this chapter. This usually occurs in informal conversations, for example, during a coffee break between organisational members. Therefore creating such environments within the departments and between departments could facilitate learning processes.

6.4. Theoretical contribution

This study makes theoretical contributions in a few major ways. First of all, this research extends and enriches the theoretical conceptual model introduced in this study which is grounded in the current literature. In doing so, this study enriches and expands the understanding of the dynamism of decision-making processes in data-intensive environments by providing an understanding of the appropriate approaches to decision-making in big data environments. It provides a better understanding of the changes required in decision-making processes in order to make them faster and more efficient in big data environments, which is highlighted in the first major theme of the study that emerged from the data. It contributes to decision-making theory by providing insights into dynamic decision-making in the context of big data and a better understanding of organisational strategies for working with and leveraging value from big data.

This study provides a better understanding of the drivers of changes required in big data environments to enhance the dynamism of decisions. In doing so, this study enriches and extends the theoretical understanding of dynamic capabilities that are required to address changes and cope with dynamic environments. It contributes to dynamic capabilities theory in coping with increasingly dynamic environments in three major areas, including corporate, individual and interpersonal levels. It particularly highlights the importance of the meso level (as an important source of dynamism within organisations in big data climates) in developing and utilising dynamic capabilities in order to facilitate the flow of information.

6.5. Implications for practice

The findings of this study have important implications in terms of practice for managers and data analysts who are involved in decision-making processes either at the individual or corporate levels. Those decisions include operational, tactical and strategic decisions. Particularly, for the practical aspect, it contributes to guiding practitioners in evaluating their organisations to inform improvement to become better enabled for big data-driven decision-making.

This study provides managers with a better understanding of the capabilities they need to facilitate the flow of information within their companies. The findings of this study provide a framework for managers to evaluate their organisational design to gain a better understanding of the changes that might be required in order to cope with big data environments.

6.6. Challenges and limitataions

This section brings to the fore some of the major challenges and limitations of this study that were encountered during the study.

Access to companies: access to companies was possibly the most challenging part of this study. This was mainly because of two reasons. Firstly, the data collection stage was contemporary with the Covid-19 pandemic that significantly affected organisations and their operations. Therefore collaborating with researchers was not among the top priorities of those companies. In addition, the pandemic, campus closure, and lockdowns also affected the research within universities and also the personal life of the researcher.

Secondly, potential participants for this study include managers and data analysts, mostly who are usually very busy with their work and do not get much free time to meet others from outside their organisations. Plus, even if they are willing to participate, they are more cautious about talking about data processing mechanisms within their companies in order not to violate their companies' policies and also DPA (Data Protection Act, 2018), although they were informed that this study has nothing to do with their companies data and information, and their personal information and company names would remain anonymous according to the university data regulation policies and research ethics.

Johnson (1997) believes that the accuracy of understanding participants' thoughts, opinions and beliefs is of high importance. This is because bias in qualitative research is inevitable and it might creep into the results, not only in the interview (data collection process) but also in reporting stage as well. However, in order to reduce the researcher's bias as much as possible, the researcher has tried to remain neutral in all stages of the report.

Analysing a huge amount of qualitative data is challenging. Using software analysis purposes might be useful, but for this study, the researcher found it challenging to analyse qualitative data with software; therefore, the analysis was carried out manually.

Theoretical sampling and generalisation: it might be assumed that cases are not representative of a specific population. In response, it could be argued that this kind of study does not test a theory which requires a representative sample. However, cases are selected based on some criteria, including the level of appropriateness and illumination to study the relationships and logic among constructs (Eisenhardt and Graebner, 2007), and generalisations are made to the theory rather than the population.

The cases of this study are limited to the companies located within the UK, and other countries or the ones who are operating internationally might need to be studied to see if they yield the same results.

There was a time constraint element involved as there was a limited time period to collect the data within the period approved by the Ethics committee. As the data collection process was very time-consuming, more cases could not be included and studied as they could potentially increase the validity of findings even more.

Communication with participants was mainly through telephone or online because of the pandemic and social distancing rules in place which limited the effective communication that could be achieved via in-person meetings.

6.7. Avenues for future research

This study has built a number of theoretical concepts regarding the main research question that are grounded in empirical data. On the ground that this study is a qualitative and inductive study and does not generalise the findings to the population, the findings of this study, including the theoretical constructs and the relationships between them, need to be empirically tested and validated. This could be carried out via a quantitative study with statistical sampling. In addition, other mixed methods could also be conducted in this regard.

Another similar study could be conducted on one case study over a longer period of time in order to gain an even deeper understanding of the concepts in relation to other organisational elements in more detail.

Similar studies could be conducted in different contexts to see to what extent this study's findings are context specific. For example, similar studies could be conducted in other countries to evaluate the impact of regional factors as well. In addition, similar studies might focus on one specific sector to be more specific about factors influencing that particular industry.

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Appendix

Appendix A: Participants information sheet

PARTICIPANT INFORMATION SHEET

Manchester Metropolitan University

Decision making in data-intensive environments and its impact on organisational design: Dynamic capabilities approach

PhD Researcher: Hadi Karami

MMU Email address: hadi.karami@stu.mmu.ac.uk

Invitation to Participate in this Study

You are cordially invited to participate in this PhD research study. Before you decide whether or not to take part, it is important for you to understand why the research is being conducted and what it will involve. Please take a few minutes to read the following information carefully.

Purpose of the Study

Due to emergence of advanced technologies especially in the fields of information, communication and data science, business environments have become dynamic and data-intensive with exponential data creation. This issue results in in the process of decision-making to become more dynamic on the ground that information coming from external sources plays an important role in decision-making processes. Adaptation to these changes to better make sense of decisions requires changes in processes of decision making in this specific context (data-intensive). Hence, this study aims to understand how decision makers change their decision-making processes, and which factors they consider important in driving those changes, and finally to develop a framework to enable decision makers to assess and improve their strategies for adapting to data intensive environments.

Research Design

In order that the research could be conducted, your organisation has been chosen as one of the cases of study. Data will be collected using face to face interviews either in person or on Skype. The data collection stage will take approximately 2-3 months during which time you will be asked to participate in an interview. The interview will be digitally recorded, with your consent.

Participation in the Research

You have been asked to participate in the research study because you were purposively selected by the researcher as a key individual who can provide valuable insight into understanding the decision-making processes in data intensive environments (Big Data context). Approximately 3-4 people from your organisation will be asked to participate in the research. Your contribution is entirely voluntary. If you do decide to take part, you will be given this Information Sheet to keep and be asked to sign an Interview Consent Form. If you give consent, you will be asked to participate in a one-to-one interview with the researcher and you will be asked a series of semi-structured questions primarily based on how big data influence your organisational decision-making processes, design and structure. Your interview will last approximately forty-five minutes to one hour. **The anonymity of your responses is guaranteed and will be treated in strict confidence.** The interviews will be conducted during working hours only and there will be no costs to you personally.

The organisation has not influenced your selection to take part in the research study in any way. Although you have been purposively selected by the researcher to participate, you should not feel obligated to take part because of the role you play in the organisation. However, it would be extremely helpful to the research if you felt you were able to participate. If you do give consent, you will be free to withdraw at any time and without giving a reason.

Potential Benefits

There are no direct benefits to you for participating in the research. In terms of corporate benefits, the research findings may enhance your organisation's ability to undertake future reforms more effectively.

Confidentiality

All information collected about you will be kept strictly confidential (subject to legal limitations). Confidentiality, privacy and anonymity will be ensured in the collection, storage, analysis and publication of research material always. The data generated during the research must be kept securely in paper or electronic form for a period of minimum of five years after the completion of a research project, in accordance with Manchester Metropolitan University's research guidelines. In compliance with General Data Protection Regulations 2018, all fieldwork data will be securely stored on a security encrypted university network.

Opt in and out to the Research

If you wish to opt in to the research, please sign the Interview Consent Form and hand it to the gate keeper in your Company. You will then be offered a convenient day and time to take part in the research. Remember, you can opt out of the research at any time, without giving a reason. If you decide to withdraw from the study, please inform the researcher by sending an Email.

Note that If the participant decides to withdraw from all components of the research, the principal researcher will discontinue all of the following activities involving the participant:

- Obtaining the identifiable information about the participant
- Collecting or recording the additional data for the interview

In addition, any identifiable data collected from the participant will be destroyed. Subject to ethical approval, data collected in relation to the participant may be retained and used for the purposes for which consent has already been given provided that they are effectively anonymised and no longer identifiable.

Results of the Study

On completion of the study, the results will be incorporated into the PhD thesis and presented to the viva committee. As a Participant, you will receive a copy of the results, if you choose to receive.

Organisation of the Research

I am conducting this research as a full-time Doctoral researcher, in the Department of Operations, Technology, Events and Hospitality Management (OTEHM) at Manchester Metropolitan University. The research study will be conducted under the guidance and supervision of:

1. Dr Sofiane Tebboune (Director of Studies): Department of Operations, Technology, Events and Hospitality Management (OTEHM), Manchester Metropolitan University.
   6.27a Business School, Manchester Campus, Oxford Road, Manchester M15 6BH, Tel: +44 (0)161 247 6692, s.tebboune@mmu.ac.uk

2. Dr Diane Hart (First Supervisor), Department of Operations, Technology, Events and Hospitality Management (OTEHM), Manchester Metropolitan University.
   6.27 Business School, Manchester Campus, Oxford Road, Manchester M15 6BH, Tel: +44 (0)161 247 4629, d.hart@mmu.ac.uk

Contact Details

My contact details can be found at the top of this Information Sheet. Please feel free to contact me, on my mobile, during the research study.

Thank You

Thank you for taking the time to read this Information Sheet. If you have any questions, please contact me and I will be happy to answer them.

Name: Hadi Karami

Date

Appendix B: Consent form

CONSENT FORM

Manchester Metropolitan University

Title of the project: **Decision making in data-intensive environments and its impact on organisational design: Dynamic capabilities approach**

Hadi Karami, PhD Researcher

MMU Email address: hadi.karami@stu.mmu.ac.uk

Participant Identification Code for this project:

Please initial box

1. I confirm that I have read and understand the Participant Information Sheet for the above study and have had the opportunity to ask questions. ☐

2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving reason. ☐

3. I agree to take part in the above study by being interviewed. ☐

4. I agree to the interview being audio recorded. ☐

5. I agree to the use of anonymised quotes in publications. ☐

6. I do not give permission for my interview recording to be archived as part of this research project, making it available to future researchers. ☐

7. I understand that at my request a transcript of my interview can be made available to me. ☐

________________________ ________________ ______________________

Name of Participant Date Signature

___________________________ ________________ ______________________

Name of Researcher Date Signature

To be signed and dated in presence of the participant.

When completed: 1 copy for participant and 1 copy for researcher.

If you provide consent to the interview, kindly fill in with your contact information to receive outcomes

of the research later:

E-mail address ____

Postal address ____

____

____

Appendix C: Interview Questions

- Can you tell me a little about your role in the organisation? How long you've been in that role?
- Can you tell me a little about your perception of big data and also what types of data your company is using for its decision-making processes? Structured or unstructured?

Decision-making

This interview is about decision-making using big data – typically the sort of decisions that have a lot of data attached, a range of data, and time pressure (velocity, volume and variety)

- Can you tell me about the sort of decisions you might be made using this data and the time pressures you experience?
- Can you tell me where the level of decisions resides – do you make the final decision? How free are you in making those decisions? How has this evolved since you have been working with big data?
- What challenges have you faced while integrating big data into your decision processes, and how have you tackled those challenges?

Capabilities

- Can you talk to me a bit more about how your own decision-making capabilities have evolved now you're dealing with big data? Did you need any training?
- Which factors or capabilities (either individual or corporate) you consider the most important in reaping the value from big data and why?

Changes in structure and authority

- How is knowledge coming from big data being exchanged among decision-makers or departments? The mechanisms, formal or informal? What's the role of productive dialogue?
- What's the perception of employees towards big data and data-driven decisions, and how can this be improved? (analytical culture and role of leaders)

Open questions at the end

- Is there anything else that you may want to add regarding the impact of big data on your organisational design, power structures and knowledge management?

Appendix D: Overview of the thematic analysis