SCHOOL OF ECONOMICS AND MANAGEMENT

LUND UNIVERSITY

The Role of Managers in Big Data Analytics

How different skills and management styles contribute to improving firm performance using Big Data Analytics

Oliver Bailey

Lorenzo Clavarino

MGTN59 - Spring Semester 2023

ABSTRACT

Insights from Big Data can become sources of competitive advantage and a foundation for decision-making, leading to an extended use of such technologies in many firms' departments. Even if it is common practice to invest in BDA, oftentimes these techniques are not exploited correctly, resulting in an unrewarded effort by companies (Dahiya, Le, Ring & Watson, 2022). Research has contributed to exploring the positive business impacts that the implementation of BDA brings (Raguseo & Vitari, 2018), however, the role of managers that are directly responsible for the BDA-related operations and decision-making has been scarcely addressed. With this research, we aim to understand the role of managers regarding BDA, and what they perceive as the value they contributed in terms of business performance. We have adopted a qualitative analysis approach, alongside an inductive approach that has helped us understand the managers' perspectives in using BDA to improve firm performance. The findings that were identified include key challenges that managers face using BDA, an interdependent relationship between essential hard and soft skills for managers of BDA, support of a BDA Resource-Based View framework, beneficial traits of managerial styles and positions in using BDA as well as future trends in BDA adoption and the future integration of Artificial Intelligence (AI) in BDA technologies.

List of figures

List of tables

1. Introduction

The introduction to this thesis will explore background knowledge and applications of BDA as well as our interest in researching BDA from a managerial perspective. Subsequently, this chapter will include the background, the purpose of our research, our research questions, and delimitations of the thesis.

1.1 Background

Data is repeatedly being created, shared, and stored through channels such as tools, people and machines (Maritz, Eybers & Hattingh, 2020). The means by which that data is created and shared is exponentially growing as new technologies and digital platforms emerge, and the potential value of data increases concurrently as datasets grow larger (Maritz, Eybers & Hattingh, 2020; Verma & Bhattacharyya, 2017). Once datasets reach a certain analytical complexity, due to their size, format variation, and the speed at which data is generated, it becomes too complex for standard analytical methods (Sagiroglu and Sinanc, 2013). This type of data is referred to as "Big Data" and requires a different analytical approach which is referred to as "Big Data Analytics" (Sagiroglu and Sinanc, 2013).

Big data is considered to be a disruptor in many aspects of organisations and can be a useful tool in making scientific advancements while also making organisations more profitable and financially efficient (Almeida & Calistru, 2013; Maheshwari, Gautam & Jaggi, 2019). The use of BDA enables organisations to combine and integrate larger datasets to gain new insights that were not possible before as it goes beyond observing and analysing single datasets one at a time (Gong & Janssen, 2020). McAfee and Brynjolfsson (2012) view BDA as the next "Management Revolution" and worldwide investments in BDA amongst organisations have been exponentially increasing as businesses search for sustainable competitive advantages achieved through better BDA capabilities (Akter, Wamba, Gunasekaran, Dubey & Childe, 2016; Maheshwari, Gautam & Jaggi, 2019). The benefits of using BDA within organisations are illustrated by the literature as being a powerful and useful asset for organisations (Akter et al. 2016; Ferraris, Mazzoleni, Devalle & Couturier, 2018; Gong & Janssen, 2020; McAfee & Brynjolfsson, 2012).

According to Alrumiah and Hadwan (2021), BDA is a useful asset to any organisation as big data can be utilised in predictive analytics, allowing businesses to equip decision-makers with predictive powers that allow them to accurately predict and capitalise on consumer behaviour. This notion is corroborated by Gupta and George (2016) who identify four capabilities of BDA as a firm resource: traceability, predictive, decision support, and analytical capabilities. Obitade's (2021) findings show that with the deployment of BDA, organisations are able to leverage the predictive and analytical capabilities of BDA to either create or uncover new marketplace knowledge. Aligned with this, Obitade (2021) also highlights the value of BDA's decision-making capabilities as being an important factor in improving the application of accumulated knowledge within a firm to create greater business value.

The benefits and uses of BDA become apparent as the application of BDA within an organisational setting sheds light on insights that are extremely valuable for the performance of any given organisation. This lays the foundation for our interest in studying this subject and exploring aspects of BDA research that remain unexplored. The applications and benefits of BDA seem to be plentiful, yet there are challenges and difficulties that come with utilising BDA in firms. There are issues related to the size and speed of BD as it is costly to store and collect, but it is also costly to develop BDA tools, solutions, and expertise that enable firms to generate insightful predictions (Almeida & Calistru, 2013; Gong & Janssen, 2020; Ferraris et al. 2018). The challenges of BDA will be explored to a further extent in section 3.3.

1.2 Purpose of Study

As there is a qualitative research gap in BDA from the perception of managers, the opportunity has presented itself to inductively research this area of BDA and firm performance. Hence, the purpose of this study is to provide a deeper understanding of managers' roles in utilising BDA and improving firm performance by investigating how different managerial skills and styles influence their use of BDA in firms. The research questions are constructed with the aim of fulfilling this purpose and ask:

RQ1: What skills and managerial styles are more appropriate for managers that work with BDA?

RQ2: How are those skills and styles influencing managers' abilities in utilising BDA to improve firm performance?
RQ3: What are the current and future challenges and opportunities in the use of BDA, and how will they impact the role of managers?

1.3 Delimitations

As we intend to investigate the research question with the purpose of creating a deeper understanding of this given topic from the managerial perspective, a natural delimitation of this study will be to structure and format our interviews with the aim to only provide data from the managers' perspective. Additionally, as Almeida and Calistru (2013) discussed, BDA solutions are costly to develop. As such, the financial resources of the firms that our interviewees represent may vary, and therefore, the BDA capabilities may vary too. As such, given that variations of BDA capabilities may change the perceived implications of BDA applications and use from the managers' perspective, the findings may be subject to firm size and financial resources that the firm is able to allocate to its BDA capabilities. Given our research purpose, we have decided to delimit the research of this thesis to only analyse the perceptions of the managers without considering the firms' size or financial resources that have been allocated for BDA purposes.

Furthermore, the selection of respondents for this study is from Nordic countries as this enables us to focus on the skills and styles of managers and how it influences how they perceive the application and use of BDA. The cross-industry selection of respondents allows for higher precision and more in-depth analysis based on greater nuance and variation of managerial skills and styles. Additionally, the geographical demarcation of the respondents allows for a larger focus on the possibility of other cultural variations that are not related to the characteristics of interest which would ultimately affect the conclusions drawn from this study.

2. Method

In this chapter we will describe the methodology applied to this research and the motivation for this choice. We will show how the data collection procedure has been conducted and how this information has been analysed. There will be a description of the interviewees' professional roles, firms, and industries, listing the respondents but also reporting the differences between them. The tools used during the research process will also be reported, alongside their role in the analysis.

2.1 Research Design

The choice of a research design is taken considering the aim of the research and the suitability of the research question. According to Sekaran & Bougie (2016) the research design helps cover the research strategies, the interference of researchers, the location, the time frame, and the level of analysis of data. The elements of a research design are the research strategy, the extent of researchers' interference, the study setting, the unit of analysis and the time horizon (Sekaran & Bougie, 2016).

For the choice of research strategy, we considered the division made by Saunders, Lewis and Thornhill (2009) who present a descriptive, explanatory or exploratory design.

The descriptive design mostly entails a quantitative approach and a defined perspective that the authors must have to draw conclusions (Saunders, Lewis & Thornhill, 2009). The exploratory design is used to analyse the cause-and-effect relationship between variables and is often subsequent to descriptive studies. Moreover, the explanatory design needs to include a hypothesis which will then be confronted with the results.

Yet, the research questions we needed to answer and the point of view we wanted to adopt for this research did not match these types of designs (Saunders, Lewis & Thornhill, 2009). The explanatory design was thus the ideal choice for this research, as it aims at studying new phenomena or using a different angle to study a topic. This design is also suitable for studies that aim at gathering various and heterogeneous information about a subject, allowing for the use of a wider scope to then funnel the information into findings. This design is indicated for qualitative methods and allows for a more unstructured outline compared to the other two.

We aim at maintaining a low interference, studying the position that managers have regarding the use they make of BDA. The type of research we are conducting is therefore not intended to determine a causality between the managers and the firm's performance, but it is more oriented towards inductively establishing correlations between managers' skills and styles and the use of BDA in their professional role (Sekaran & Bougie, 2016).

The research is developed in a non-contrived study setting since it aims at gathering insights that can then be processed to develop conclusions regarding managers' use of BDA. The study will be conducted as a cross-sectional one (Sekaran & Bougie, 2016), meaning that the interviews were collected in roughly a month and the information gathered once. We will not study any changes over time in the career of managers.

2.2 Research Approach

When it comes to research approaches, the choice mainly points to two main cores: deductive reasoning and inductive reasoning, both of which are considered to be applicable to both qualitative and quantitative research (Sekaran & Bougie, 2016). The deductive approach aims at testing a theory of a determined subject. The procedure for this approach starts from the general theory and proceeds by listing possible hypotheses that can be verified. This leads to a set of observations that serve as tests to demonstrate the determined hypotheses. The analysis of these results allows for the rejection or confirmation of the chosen theory; Bryman and Bell, (2015) define this approach as theory-driven. This method has been mainly used in quantitative studies and is thus less suitable for the type of research we are conducting (Sekaran & Bougie, 2016). The wide scope of our study would clash with the strict guidelines required to operate with a deductive approach, leading to partial and possibly unsatisfying results.

The inductive approach works the opposite way, since it starts with the observation of a phenomenon, analysing the details that compose it and then proceeding with the formulation of general results.

2.3 Justification of research method

The two choices available for research methods are qualitative and quantitative (Bryman & Bell, 2015). Our decision was to apply a qualitative method since it gave us the possibility to investigate the profile of the manager and the use of BDA, matching with the inductive approach we decided to use. A quantitative method would be preferred in cases with larger population samples and the chance to collect and analyse data that is already categorised before the collection. Working on the research design, we considered the possibility of using surveys to then analyse possible correlations, however, it was difficult to apply due to time constraints, a geographically limited sample and a research question that does not fit with this method (Bryman & Bell, 2015). The intent of this thesis is to provide a closer look at how managers use BDA and whether certain managerial styles and skills influence this use. For this reason, we are conducting research in a qualitative nature to capture the human elements more in-depth.

The inductive approach starts with the observation of a phenomenon, analysing the details that compose it and then proceeding with the formulation of general results. Since we are analysing the connections between the growing phenomenon of BDA and its entanglements with managerial aspects, we can confirm that this would be the appropriate approach (Sekaran & Bougie, 2016). Additionally, since BD is a relatively recent development, and the "few" publications that relate to a managerial perspective, choosing a qualitative and inductive approach provides adequate circumstances for us to engage in this phenomenon in a deeper context which allows us to capture the nuances and the subjective experiences of each respondent (Woiceshyn & Daellenbach, 2018; Locke, 2007).

2.4 Selection of Respondents

The selection of respondents was based on their involvement in the handling of Big Data within the firm. The companies involved in the study are therefore using Big Data in their operations, which is the main criterion for their selection. The research aims at defying the managerial role in the context of BDA, hence companies that don't use such technologies or have only planned to implement them, were not considered.

Considering our research questions, and the inductive research approach, we aimed at reaching specialists from different companies that operate in different industries. As the target of the study focuses on the role of managers, collecting data from professionals that work in similar roles but operate in different industries, would provide us with a wider scope. The industries and sizes of the companies are visible in Table 1.

Table 1. Respondent information

Participant	Professional role	Format of interview	Interview date	Education	Industry	Size of the firm in terms of employees
R1 - Maersk	Head of Data Pricing Data Science	Zoom	21/04/2023	MSc. Informatic and Statistics	Shipping	110000
R2 - EQT, Klarna	Data Science Manager	Zoom	28/04/2023	MSc. Engineering Physics, and Applied and Computational Mathematics	Private equity, Online payment systems	1200/5800
R3- Google	Head of Cloud Technology	Zoom	04/05/2023	MSc. Computer Science, and International Business	Cloud Solutions	135000

R4 - Electrolux	Data Engineering Team Lead	Zoom	05/05/2023	MSc. Engineering and management of Information Systems	Home Appliances	51000
R5- Tetra Pak	Decisions & Data Science Manager	Tetra Pak Office	08/05/2023	MSc. Engineering Physics, and Theoretical Philosophy	Food Packaging & Processing	25000
R6- Tetra Pak	Leader for Sales & Marketing of Automation & Digital Solutions	Zoom	26/05/2023	BSc. Engineering	Food Packaging & Processing	25000
R7 - Scania Group	Head of Data Analytics	Zoom	25/05/2023	MSc. Vehicle Engineering	Vehicle Manufacturer	54000

In addition to the collection of the data through interviews, we also attended a conference held by IKEA data scientists, organised by LAMBDA (Lund Data Science Society) on the 26th of April 2023. The attendance and consequent engagement with this activity were not considered as collected data but as a source of additional information that was highly relevant to the thesis topic. The conference consisted of a Q&A, where the data scientist gathered questions from Lund University students and organised replies over a two-hour presentation. The discussion was centred on the firm's use of BDA models and the tasks that were assigned to the manager. During the fourth chapter of this thesis, some of these insights will be combined with our own findings.

2.4.1 Differences Between Professional Roles.

The respondents we decided to target are intentionally heterogeneous. We are aware of the differences between education, professional titles, responsibilities, and skill sets; however, as the research questions are designed to tackle how managers contribute to the use of BDA to improve firms' performance, the range of our research needed to be faster than other papers. The classification of the respondents mainly relies on the use that managers attribute to BDA, hence we made sure this was a key component of their and their teams' tasks. The differences in the professional roles of respondents, including their job description, responsibilities and skills, are listed in Table 2.

Table 2. Different roles within data departments (Ismail & Abidin, 2016; Gupta & George, 2016; Persaud, 2021)

Title	Job Description	Skills	Responsibilities
Data Scientist	Follows the process of generating useful data from end to end. Recommends ways to use data by building algorithmic and mathematical models.	Coding and statistical skills	In charge of solving complex problems presented in the datasets analysed.
Data Engineer	Handles a broad data set and builds structures that will be used by analysts and scientists.	Software engineering-related skills, strong coding skills (Python, Java)	Responsible for making data available and accessible for Data Scientists and Analysts.

Data Analyst	Analyses data of different sizes and variety in order to condense them into usable information for business purposes.	Interpretation of business needs and analysis of data to solve business-related problems	Discover paths that datasets are “hiding” and display them in a way that can be understood and implemented in business decision-making.

2.5 Data Collection

As previously stated, the typology of the research strategy is survey research. When considering this category, the more appropriate method for our purposes is conducting semi-structured interviews. Using interviews effectively combines the inductive approach, and the semi-structured design of the interviews helps us to gather more information about the topic (Sekaran & Bougie, 2016). The data extracted from the interviews can be considered as a primary source since the research relies on those to build results. At the same time, there is a set of secondary sources such as academic papers and newspaper articles, that we have used to sharpen the structure of our interview guide (Bryman & Bell, 2015).

Semi-structured interviews are suitable for assessing broad problems, allowing us to add some follow-up questions and further develop additional topics of importance (Sekaran & Bougie, 2016). Saunders, Lewis and Thornhill (2009) highlight how the use of semi-structured interviews can lead to bias in the integrity of data, especially regarding the comparisons intended. While aware of these risks, we still maintained our choice, yet we took the liberty of slightly adjusting some of the secondary questions according to the professional role of the interviewee, which allowed us to collect on-point data without the risk of collecting different and biassed data. Risks in data comparison are mitigated by the semi-structured setting, especially when studying a heterogeneous selection of respondents (Queirós, Faria & Almeida, 2017). There are also other caveats for this method, like the time consumption of the data collection; however, the research calls for in-depth results that could not be achieved any other way (Maxwell, 2013). The research questions this thesis poses are intended to investigate the role of the manager through inductive lenses which allows for more nuanced and richer data compared to a purely quantitative approach (Maxwell, 2013).

We intended to conduct one-on-one interviews and, considering the geographical position of the interviewees proposed that the meetings be conducted either online or over the phone. We expressed our preference for the video and audio formats to our candidates as it seemed more appropriate to gather more non-verbal communication from the side of the interviewees. Telephone interviews are not the best format for semi-structured interviews, as interviewees tend to prefer a concise dialogue with direct questions (Sekaran & Bougie, 2016). Other disadvantages of this method are also the impossibility to read the non-verbal communication of the interviewees, and the nuisance of having to provide phone contact information (Sekaran & Bougie, 2016) which we are able to avoid with video calls.

2.5.1 Interview Guide

The structure of the interviews was divided into different topics and phases. First, there was a presentation phase, where the interviewee was introduced to the study and had the chance to present her/himself, the role in the company and give general information about the firm. Subsequently, the interview shifted towards questions related to the use of BDA in the company and what the perception of the manager was. This part also included what skills managers consider as important when using BDA, and what soft and hard skills their role requires. The interview continued by considering the influence of BDA on the different performance indicators of the company, including a description of what the role of the manager may be in the implementation of BDA to improve the firm's performance. Finally, some questions regarding the future, such as the use of BDA in the company, the changes it will bring to the industry and how will managers need to adapt to this phenomenon were included.

2.7 Thematic Data Analysis

The process before the analysis of data consisted in recording the interviews, with the consent of the interviewee, and transcribing the audio file using the software Otter.ai. We did this operation right after the data collection, as waiting for the collection of the data to be completed would have not allowed us to inductively conduct some adjustments and considerations (Johnson, Adkins & Chauvin, 2020). The process of data analysis information is what allows researchers to distil theory from data analysis. In Sekaran and Bougie (2016) this process is divided between data reduction, data displaying and the formulation of conclusions (see Figure 1). We used the framework reported by Miles and Hubermann (1994) to summarise the data analysis process in the different steps (Figure 1). Following these steps, once the transcription was completed, the interviews were cleaned and analysed in order to be coded according to a thematic analysis approach. A commonly used approach to doing an inductive thematic analysis is Braun and Clarke's (2012) method. This method is performed by following a six-step process:

1. Familiarisation of data
2. Generating codes
3. Generating themes
4. Reviewing themes
5. Defining themes
6. Identifying patterns and locating exemplars

Braun and Clarke (2012) argue that through iterative cycles of reading the collected data, more insights are extracted as one becomes more familiar with the data. Additionally, by generating codes, the researcher can generate codes for as many topics as possible and apply the codes to contextual segments. Through the generation of themes, researchers are able to sort the codes by using illustrative techniques such as matrixes and tables. By doing this, the researcher can determine the fit of the data and identify the need for sub-themes if the fit of the data is insufficient. Furthermore, as the themes are generated, reviewed and defined clearly, the researcher may produce results which are effectively illustrated and visualised through the thematic analysis approach where patterns are finally identified and connecting examples are located. Braun and Clarke (2012) argue that there is no set proportion of a researcher's dataset that requires a distinct connection to certain themes for this evidence to be considered a theme. This means that even though only a minority of the data can be connected to a theme, the purpose of the theme is still there to address the research question.

The coding was conducted through the platform NVIVO, which helped in the process of defining the parts of interviews that best fit the chosen categories, organising them and then visualising the correlations and insights that could then be the foundations of our results (Johnson, Adkins & Chauvin, 2020). The coding process also allowed us to accelerate in the final phase: drawing a conclusion from data.

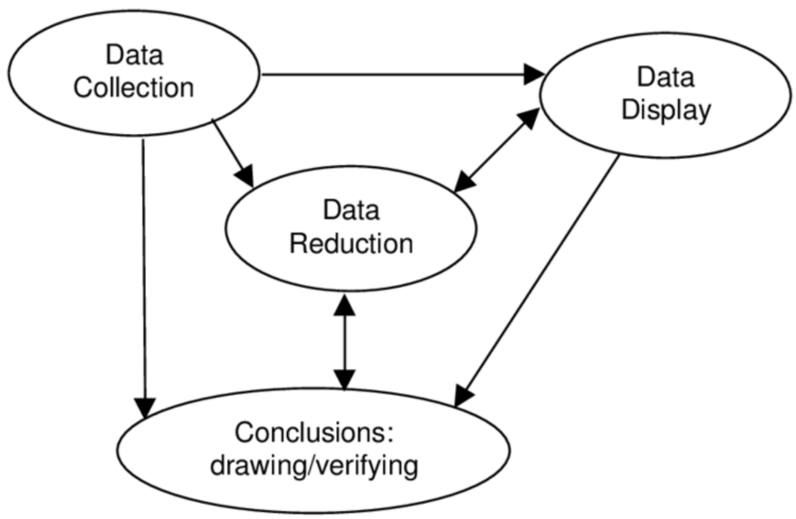

Figure 1. Framework for Qualitative Analysis (Miles & Huberman, 1994)

2.8 Trustworthiness

Establishing trustworthiness in qualitative research is an imperative part of generating credible and meaningful results (Nowell, Norris, White & Moules, 2017). For qualitative research to be trustworthy, authors should demonstrate high levels of precision for the data analysis by disclosing the details of the method in such a way that the reader can determine the credibility of the research process (Nowell et al. 2017). As we are pursuing a thematic analysis method, we will adopt certain measures of the step-by-step framework of establishing trustworthiness in thematic analysis proposed by Nowell et al. (2017) and Braun and Clarke (2012) to ensure trustworthiness in the results that our analysis will produce.

In each of the six phases of the thematic analysis approach, Nowell et al. (2017) have proposed certain actions that researchers may take to ensure credibility, transferability, dependability and confirmability. In addition, Nowell et al. (2017) emphasise the value of audit trails and consider reflexivity in the research process. Audit trails are evidence for readers of the decisions that reflect the use of theoretical and methodological approaches throughout the research process (Nowell et al. 2017). These decisions require clarification and rational arguments if the trustworthiness of the research is to be adequately sufficient. Consideration of reflexivity is part of the audit trails and can aid in establishing evidence for certain decisions regarding the theoretical and methodological decisions of the research process (Nowell et al. 2017).

Credibility refers to the notion that data has been interpreted correctly where the fit of the respondents' view and the interpretation and representation of the researcher is adequate (Bryman & Bell, 2015; Nowell et al. 2017). To establish credibility, we will with the help of peer and respondent debriefing ensure that our interpretation of data seems to be credible. Transferability is concerned with the generalisation of the findings of the research, where the transferability of the findings is often contextual in qualitative research (Nowell et al. 2017). However, to mitigate the issue of transferability, we have intentionally delimited our selection of respondents to only be from Nordic countries which eliminates certain cultural variables that may affect the results of this study. This will produce a more generalizable context of our findings which is transferable for the interest of Nordic stakeholders. Furthermore, dependability can only be achieved through logical and rational documentation of the research process (Nowell et al. 2017; Bryman & Bell, 2015; Braun & Clarke, 2012). This entails that choices made during the research process are well documented and argued for in a rational manner. We have disclosed our choices of theory and method, as well as our interpretation of our findings with the aim of fulfilling the criterion of achieving dependability.

Confirmability is an additional criterion for the interpretation of the derived data where the authors of qualitative research are able to clearly demonstrate how the interpretation of data has been performed (Nowell et al. 2017; Bryman & Bell, 2015). Through reference to our theoretical framework as well as derived examples of the raw data, we aim at fulfilling this criterion.

2.8.1 Reflexivity

Reflexivity is related to the acknowledgement of the role of the researcher in conducting research (Watt, 2007; Thyer, 2010). As this thesis is of a qualitative nature, we become a natural part of the research process as our prior experiences, beliefs, and assumptions may affect the outcome of the research (Watt, 2007). Consequently, an important part of conducting qualitative research is critical assessment and reflection on the position that the authors have in regard to the research (Watt, 2007). This critical reflection is concerned with the reflection of the political, social, cultural, and ideological biases of the authors as well as those of the interviewees (Watt, 2007). These assumptions may influence the choice of method, the data collection and analysis, as well as have implications on the overall findings of the research (Watt, 2007).

We acknowledge that the selection of the research method and parameters may have been influenced by previous research conducted on similar topics, however, we are also aware of this as the approach to our research aims at targeting a gap in the existing literature. The argument for selecting an inductive approach for this research is to prevent mistakenly narrowing it down to specific theoretical assumptions and maintain an objective and broad view of the topic (Woiceshyn & Daellenbach, 2018; Locke, 2007). We believe that this approach will minimise the risk of bias from our own perspective as we are openly interpreting the perceptions of the interviewees as we interview them. However, this is not to say that the thematic categorization and review of the data will completely avoid our own bias as this categorization will be based on our own interpretation of the data and theoretical frameworks that are used.

Furthermore, there is also the notion of interviewer bias which could possibly distort the outcome of an interview (Salazar, 1990). Through the process of interviewing, the interviewer can identify issues and a wider range of opinions and behaviours that are relevant to the topic of research (Salazar, 1990; Creswell, 2017). Interview bias entails that personal qualities are generally considered to be determinants of the outcome of an interview, meaning that biases introduced by the interviewer may directly affect the validity and reliability of the data (Salazar, 1990). To avoid causing interview bias and affecting the validity of the data, we have applied certain techniques in our interviews which Salazar (1990) discussed in her paper. These techniques include open-ended questions, avoiding suggesting inference or making conclusions about the respondents' answers mid-interview, and balancing each specific theme of inquiry evenly to avoid the suggestion of specific significance for certain themes.

2.8.2 Ethics

To ensure adequate ethical standards for this thesis, we have conformed to the standards of the European Code of Conduct for Research Integrity (European Science Foundation, 2017). The purpose of adopting these ethical standards is to ensure a balance of the search for new knowledge and safeguarding the interest of the research's participants. In this case, the participants that require safeguarding are the interviewees that have participated in this study with the expectations of having their identities kept anonymous and for us to accurately and truthfully transcribe and interpret the interviews. To ensure adequate ethical standards for this thesis, the four principles of research from the European Code of Conduct for Research Integrity (European Science Foundation, 2017) have been adopted which can be listed as follows: a) Reliability, b) Honesty, c) Respect, and d) Accountability.

The adoption of these four principles entails that we ensure a high quality of research, reflected in the research design, methodology, analysis and use of resources. Equally so, our research and conclusions are truthful and honest representations of our findings. Furthermore, we have the utmost respect for all participants in the research process by respecting their anonymity and interview answers as well as us authors being fully accountable for the whole research process.

3. Literature Review & Theoretical Framework

During this chapter, we will account for previous research, theories, concepts, and challenges that relate to the main topics of this thesis. These concepts and theories will provide useful frameworks for how we structure our research to address some of the challenges related to BDA, as well as how we interpret the results from our data collection.

3.1 Phases of the Literature Review

The literature review started by considering papers that have analysed the BDA impacts on business, as the initial phase of brainstorming aimed at understanding the concept of Big Data and to what extent it was directly related to business performance. This led us to investigate more on what is intended for Big Data Analytics and what type of managers are involved in roles that use this type of data. Reviewing academic publications and discussing with experts in this field, helped us display the problematization part that is connected to BDA. Having established these initial concepts, we then proceeded to report literature that included a manager-oriented view of this topic, which is collected in the third section of this chapter. At this point we found it useful and inspiring to confront our progress with previous theses, which were also considering applications of BDA in business, but with different focuses. This helped us in checking and adjusting our literature review on the topic, but also in targeting literature gaps.

Finally, considering the status of our methodology section and our necessity to link it with theories, we identified the Resource Based View as the best way to address the managerial capabilities related to BDA.

3.2 Big Data Analytics

BDA and Big Data are the results of the evolution of technology and the exponentially increasing inflow and outflow of data within organisations (Verma & Bhattacharyya, 2017). These larger datasets that are emerging through the development of new technologies that collect data are regarded as Big Data as illustrated in Figure 2. Big Data (BD) is defined by IBM (2023) as assets of data which cannot be analysed through traditional analysis methods that require different techniques to be handled, unlike the standard relational databases. The definition provided by LCIA (2012) considers how this huge amount of data is often not structured using normal analytical tools. Therefore, analysing data that surpasses a certain dimension (like BD) would be impossible using traditional data analysis techniques and infrastructures (Chen & Zang, 2014; IBM, 2023; Elgendy & Elragal, 2014).

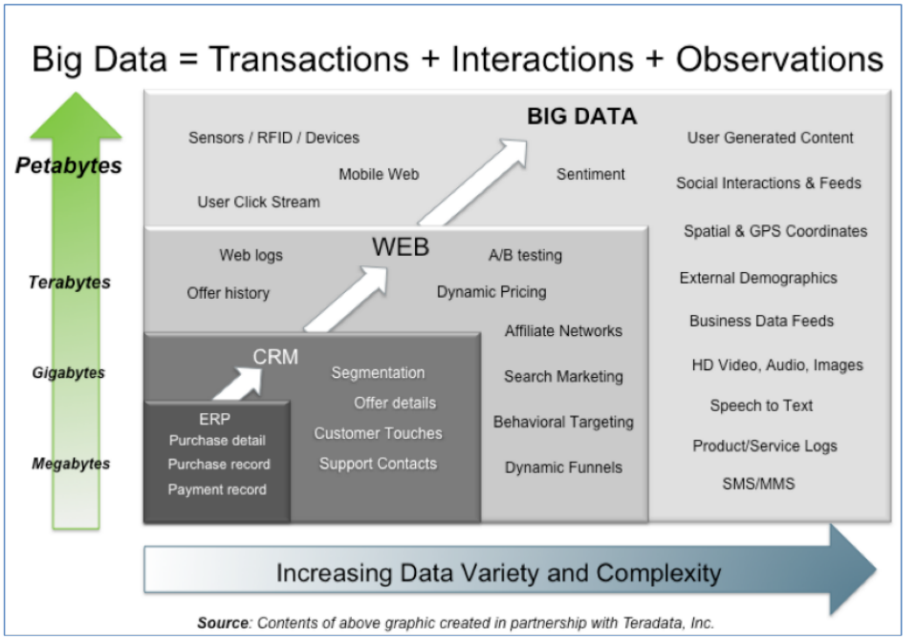

Figure 2: Connolly's (2012 cited in Alles & Gray, 2016) definition of Big Data

The growing number of technologies and tools are generating data that is increasing in volume, challenging companies that are trying to capitalise on this information (Verma & Bhattacharyya, 2017). Therefore, BDA technologies are relatively young, since this trend has been fueled by the increased use of mobile digital devices and social media, the improved bandwidth of the internet and better analytical methods (Verma & Bhattacharyya, 2017; Gandomi & Haider, 2015).

Big Data can be characterised by 3 or 5 Vs (Sagiroglu & Sinanc, 2013). The first three are Variety, Velocity and Volume (Sagiroglu & Sinanc, 2013). Variety is the characteristic that provides width to Big Data, which actually makes it "big". Big Data can be retrieved from a huge variety of sources and can be found in different formats: structured, semi-structured and unstructured (Sagiroglu & Sinanc, 2013). Each respective format becomes progressively more difficult to handle, especially with classic analytical tools and systems (Chen & Zhang, 2014). Structured data is classified as being stored in a database while semi-structured data is contained in sources like documents, social media, pictures, audio files, video, and sensor-related files. However, a majority of data comes from unstructured sources that result in larger, unstructured sets of data that cannot be processed using traditional database management tools (Cao, Chychyla & Stewart, 2015).

Volume represents the size of data, which lately has surpassed the terabyte and petabyte scale (Sagiroglu, 2013). The volume of data collected is an indicator of the possible valuable knowledge that can be scraped by the firms that possess it (Verma & Bhattacharyya, 2017).

The third V, velocity, is regarded as the speed at which data is generated (Sagiroglu and Sinanc, 2013). Velocity measures how fast data is coming in and stored, which can oftentimes happen in real-time or stored in batches of datasets (Sagiroglu & Sinanc, 2013). In theory, the higher the volume, variety, and velocity of the data, the stronger the analytical basis and more valuable the insights the data can bring (Sagiroglu & Sinanc, 2013).

From other sources, it is possible to retrieve additional elements that define Big Data, such as Veracity or Validity, and Vinculation (Verma & Bhattacharyya, 2017; Monroe, 2013; Elgendy & Elragal, 2014). Veracity or validity stands for the degree of trustworthiness of the data, characterising the consistency and completeness of data (Elgendy & Elragal, 2014; Verma & Bhattacharyya, 2017; Monroe, 2013). Vinculation, on the other hand, stresses the degree of correlation between the data collected (Monroe, 2013).

The areas of application of BDA appear to only be limited by the imagination and ability of the user, however, the core aspect of BDA is to generate predictive and accurate insights for whatever aspects of a business that is of interest to the business stakeholders (Gong & Janssen, 2020; Akter et al. 2016; Ferraris et al. 2018; McAfee & Brynjolfsson, 2012; Alrumiah & Hadwan, 2021; Gupta & George, 2016). This implies that BDA can aid firms in a multitude of ways where predictive analysis is of value, often in customer behaviour and improving internal cost and production efficiencies (Alrumiah & Hadwan 2021; Raguseo & Vitari, 2018; Gupta & George, 2016). This presents the challenge of knowing what BDA will generate insights for, and how these insights will be used, which will be discussed in the following section.

3.3 Challenges and Problematization of BDA

Ferraris et al. (2018) have highlighted the emerging literature on the capacity and ability of firms to manage, process, and analyse Big Data as well as the positive effect of BDA on firm performance. BDA plays an important role in different aspects of the management of firms, mostly by informing decision-making and is said to revolutionise existing ideas about management practices (Ferraris et al. 2018; McAfee & Brynjolfsson, 2012). However, discoveries presented by previous literature indicate that BDA by itself is not causally related to the improvement of firm performance, but rather BDA should be viewed as an effective tool to increase firm performance if used correctly (Ferraris et al. 2018; Gong & Janssen, 2020). Gong and Janssen (2020) argue that the literature on BDA understates the importance of the organisational dimension of BDA and the usage of BDA. An organisation's capabilities in regard to BDA address whether organisations have the ability to create value through the usage of BDA (Gong & Janssen, 2020). This presents the problem of the implementation and utilisation of BDA and how organisations can equip themselves to enable full capitalization on its usage.

If extracted and analysed correctly with high-quality standards, BD can be utilised in an organisational setting by eliminating certain aspects of human error (such as incorrect intuition and human bias) in managerial decision-making and therefore directly contribute to the consistency and rationality of the managers' decisions (Ferraris et al. 2018; White 2012). White (2012) however, argues that managers who are using BDA as a tool for their decision-making need to be cautious. If data is not sufficient, and the quality of the data is of a poor standard, then firms may conduct incorrect analysis of business and decision-making opportunities which naturally presents the problem of relying on incorrect data.

Almeida and Calistru (2013) have identified some other key challenges and issues of Big Data management and suggested some strategies as to how management teams of BDA can mitigate these issues. A key issue of Big Data and BDA is the substantial amounts of data points that Big Data provides. As the volume of data is expanding at an increasingly exponential rate and the development of computers handling such amounts of data is not moving at the same pace, there needs to be a shift in strategy for how this volume of data is handled (Almeida & Calistru, 2013). Additionally, as datasets are increasing in size, the time needed to analyse these datasets is also growing (Almeida & Calistru, 2013). These challenges present themselves when organisations are not equipped to mitigate such issues and are therefore unable to reap the benefits of BDA (Gong and Janssen, 2020).

Furthermore, Ferraris et al. (2018) and Obitade (2021) have discovered the intermediary role of Knowledge Management (KM) orientation in the relationship between BDA and firm performance. In the studies conducted by Ferraris et al. (2018) and Obitade (2021), KM was considered through three different perspectives: acquisition, conversion, and application of knowledge. Both studies presented a strong intermediating effect of KM between BDA which is corroborated in this quote: *"People who understand the problems need to be brought together with the right data, but also with the people who have problem-solving techniques that can effectively exploit them."* (McAfee & Brynjolfsson, 2012 p.9). This conclusion entails that leaders of organisations that have the ability to match domain expertise with the right data will be able to utilise BDA more effectively in their operations and therefore increase firm performance.

From a managerial perspective, these challenges are highly relevant as managers and IT practitioners need to collectively and selectively identify what data is of interest to them in terms of what type of decisions the data will inform and with consideration to the finite resources of the firm (Almeida & Calistru, 2013). This selective approach to the data is necessary as analysing complete sets of Big Data is unrealistic for most businesses as it is too time-consuming and too expensive as collecting, storing, and analysing the data is very costly (Almeida & Calistru, 2013). This is where the managerial aspect of BDA comes into play as there are other, restricting, elements to BDA other than just a firm's analytical capabilities that are related to the responsibilities of a firm's management team. Knowing what decisions BDA will inform, which data is of the most importance, and what amount of resources should be allocated to conducting BDA are managerial challenges and is an important intermediary to BDA's influence on firm performance (Almeida & Calistru, 2013; Ferraris et al. 2018). McAfee and Brynjolfsson (2012) argue that leadership plays a pivotal role in these challenges, as there must be someone in a management or leadership position that defines what goals the organisation is aiming to achieve through the use of Big Data.

Furthermore, a general consensus in this research is the challenge of communicating data-driven insights to business stakeholders. This issue stems from the resistance to change from changing the mindsets of intuitively driven executives and being able to facilitate communication and pedagogically illustrate insights generated from BDA to non-technical stakeholders (McAfee & Brynjolfsson, 2012; Ferraris et al. 2018; Davenport & Patil, 2012; Gong & Janssen, 2020).

Gong and Janssen (2020) also highlight the organisational challenges of BDA usage related to privacy, management capabilities, authority, and legitimacy concerns. The concept related to management capabilities includes an organisation's use of BDA, linked to the required expertise and infrastructure of BDA and management's ability to facilitate enhancements in operations performance through BDA applications. This can be linked to the literature on KM's intermediary role in BDA and the managerial aspect of selectively dedicating BDA resources considering the organisation's capabilities (Ferraris et al. 2018; Almeida & Calistru, 2013). Furthermore, the concept of authority and legitimacy revolves around the managers' need for authority to facilitate BDA actions, and legitimacy to drive organisational change through BDA applications (Gong & Jenssen, 2020).

These challenges present an empirical gap in the literature as the qualitative research on the managerial aspect of BDA usage is lacking in comparison to the empirical, quantitative research on BDA's impact on firm performance. Although the common conclusion of research about BDA is its positive impact on firm performance, certain literature that has been presented is concerned with the managerial challenges related to the usage of BDA. It is this angle of approach that we will use in this thesis as we aim to provide research on managers' perception of BDA, the implications on firm performance and how it is influenced by their managerial skills and style. By inductively studying the implications of BDA from the managers' perspective, we will be able to provide a deeper understanding of how managers that are utilising BDA perceive its utility, in general, and task-specific terms and whether or not these managers believe that BDA is a valuable resource for developing a sustainable competitive advantage.

3.4 The Relationship Between Managerial Skills and Firm Performance

Plentiful research has been conducted on the positive relationship between BDA and firm performance, the intermediary role of the manager and KM orientation on the use of BDA to increase firm performance, and the relationship between managers' level of technical skill and firm performance. However, little is known about the phenomena of managers' characteristics and the influence of this on the use of BDA and the managers' perceived implications on firm performance.

A paper by Hysong (2006) investigates the relationship between a managers' level of technical skill and the perception of managerial performance. Hysong (2006) discovered that employees perceive managers with higher levels of technical skill to be more competent and effective in comparison to managers with lower technical skills. The author argues that the relationship between technical skill and managerial performance is more prominent for managers that oversee technical functions in their organisation, with the perceived managerial performance mostly connected to the technical skill of managers, rather than other skills such as interpersonal skills and the general experience (Hysong, 2006).

Ferraris et al. (2018) find that effective management plays a crucial role in transforming BDA capabilities into firm performance by considering knowledge management. They identify the need for a Data-Driven Culture imposed by management to achieve effective use of BDA insights within a firm (Ferraris et al. 2018). However, their study's quantitative nature limits the depth of understanding of the phenomena associated with the managerial influence on firm performance.

Other literature emphasises the importance of similar managerial skills and characteristics such as strategic vision, technical knowledge, collaboration, and adaptability for managers to create value through business analytics. According to many authors, managers need a strategic vision for analytics to align initiatives with organisational objectives (Vidgen, Shaw & Grant, 2017; Gupta & George, 2016; McAfee & Brynjolfsson, 2012). Managers and data analysts also require a deep understanding of data and analytics processes while also being able to effectively communicate with experts within these domains (Vidgen, Shaw & Grant, 2017; Davenport & Patil, 2012). McAfee and Brynjolfsson (2012) stress the importance of collaboration with analytics departments and other stakeholders to address challenges and gain support across the organisation. However, none of these studies investigate how managers perceive their own influence on BDA use, or how managers perceive the effect of their characteristics on BDA utilisation.

Furthermore, published papers such as Ismail and Abidin (2016), list the main skills related to professionals that work with BDA, as well as listing the most common skills per professional role (Figure 3). Our intent is therefore not to relist these skills, but rather to consider how they serve managers and help them.

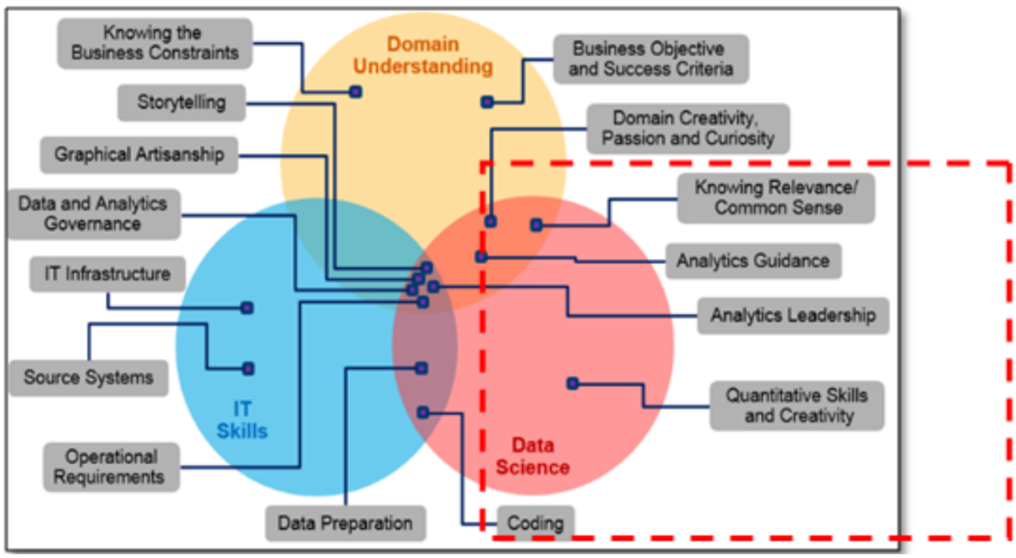

Figure 3. Classification of BDA-related skills (Ismail & Abidin, 2016)

Based on Figure 3, the skills required for using BDA can be divided into Domain Understanding, IT skills, and Data Science-related skills. Another classification by Gupta and George (2016) divides skills into managerial and technical categories. However, for a more suitable approach using semi-structured interviews, we grouped skills into Soft and Hard skills based on Balcar's (2016) definition. Hard skills are knowledge-related and trainable, while soft skills are attitudes and behaviours derived from experiences and traits (Balcar, 2016). We can recognize hard skills in the classifications by Ismail and Adibin (2016) and Gupta and George (2016), and consider soft skills like communication, leadership, and passion, as proposed by Dubey and Gunasekaran (2015) when analysing the data regarding managerial skills.

3.5 Resource-Based View

The resource-based view, or RBV, is a classical strategic framework emphasising that a firm's resources and capabilities are the main determinants of its competitive advantage (Peteraf, 1993;

Barney, 1991). The framework contributes to the explanation of long-run differences in firm profitability that cannot be explained by changes in industry conditions (Peteraf, 1993). In its essence, the RBV framework allows for managers to differentiate between resources that are of more value to sustaining competitive advantage than other, less valuable resources (Peteraf, 1993; Barney, 1991; Assensoh-Kodua, 2019). Barney (1991) argues that with resource advantages within a firm, the firm can achieve higher levels of performance with the assumption that the firm can efficiently exploit its resource advantages.

Mata, Fuerst, and Barney (1995) have created a framework for categorising a firm's level of competitive advantage based on a set of conditions. The framework illustrates how these conditions have to be met to achieve a sustainable advantage (Figure 4).

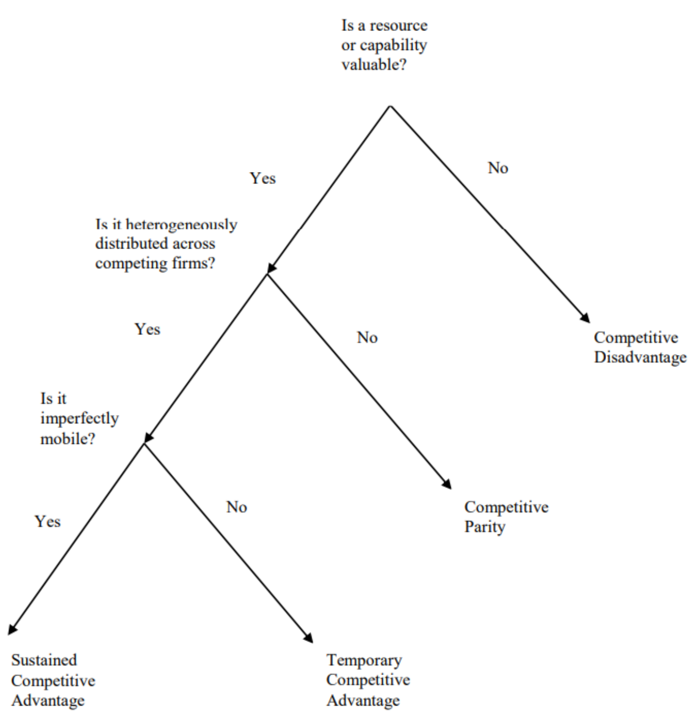

Figure 4. Identification of Resources and Capabilities (Mata, Fuerst & Barney, 1995)

According to Barney (1991), Assensoh-Kodua (2019), and Peteraf (1993), a firm has a competitive advantage when it has the ability to implement a value-creating strategy, which is exclusive to the firm. This entails that no competitors are replicating and implementing the same value-creating strategy. However, sustained competitive advantage differs from competitive advantage as it consists of a firm's ability to deter the possibility of competitive duplication of its value-creating strategy (Barney, 1991). According to Barney (1991) a resource can only aid a firm in sustaining competitive advantage from the perspective of the RBV when it satisfies these four conditions (thereby also fulfilling those in Figure 4):

a) the resource is valuable as it can exploit or neutralise threats in a firm's competitive environment,
b) the resource is rare and hard to come by,
c) the resource is imperfectly imitable,
d) there are no perfect substitutes to the resource.

For Barney (1991) valuable resources can be used to improve the efficiency and effectiveness of firms, whereas Peteraf (1993) and Dahiya et al. (2022) highlight the cost advantage that valuable resources can bring to a firm. Additionally, Bogner and Thomas (1994) argue that a sustained competitive advantage increases customer satisfaction through the use of a firm's valuable resources. However, is BDA considered to be a valuable resource that can be used to provide firms with such advantages? This topic will be discussed in the next section.

3.5.1 Resource-Based View and BDA

Melville, Kraemer and Gurbaxani (2004) and Bharadwaj (2000) have illustrated how the RBV is an appropriate framework for understanding and identifying value creation in terms of information systems (IS) and IT capabilities within firms to improve firm performance. Therefore, we believe that the RBV is a suitable theory for our study as it can help to better understand and interpret the data that we collect from the interviews and identify BDA's ability to improve firm performance by establishing a competitive advantage.

Research by Wang, Kung, Wang and Cegielski (2018) has also shown that BDA capabilities can generate business benefits from an RBV perspective. Additionally, Chae, Sheu, Yang and Olson (2014) have demonstrated that from an RBV perspective, BDA usage within organisations achieves greater market performance in comparison to competitors without BDA capabilities.

Gupta and George (2016) argue that the RBV framework builds on the idea that firms can gain a competitive advantage and increase operational efficiency by combining IT capabilities with other internal resources. However, more applicable to our thesis is the research conducted by Dahiya et al. (2022).

Dahiya et al. (2022) argue that managers are increasingly becoming aware of the important role they have in the implementation and use of BDA as BDA solutions are generally considered highly valuable resources in modern times. In their research, the authors discovered that based on the perspective of the RBV, managers can sustain a competitive advantage for a firm through firm-customised BDA applications and higher levels of data proprietorship. Dahiya et al. (2022) argue that managers may use BDA to increase the cost efficiency of a firm's operations, but should, more importantly, develop firm-specific BDA knowledge. Firm-specific knowledge is regarded as expertise and knowledge that is unique to a firm, and by developing BDA capabilities to enable the creation of firm-specific knowledge, firms can sustain a competitive advantage from an RBV perspective (Dahiya et al. 2022).

Dahiya et al. (2022) also developed a framework of BDA firm-specific knowledge and BDA application customisation (Figure 5) based on an RBV perspective, which allows for the identification of the level of competitive advantage a firm's BDA capabilities can establish. The authors argue that as firms use publicly accessible data, the insights generated by BDA are not firm-specific and therefore, not contributing to a sustainable competitive advantage (Dahiya et al. 2022). Additionally, as firms discover where the demand for data is the highest within their firm, they can customise the application of BDA-generated knowledge and increase BDA's contribution to the firm (Dahiya et al. 2022; Almeida & Calistru, 2013; McAfee & Brynjolfsson, 2012). As data proprietorship and the customization of the BDA application increases, the knowledge specificity and value of BDA insights increases concurrently (Dahiya et al. 2022).

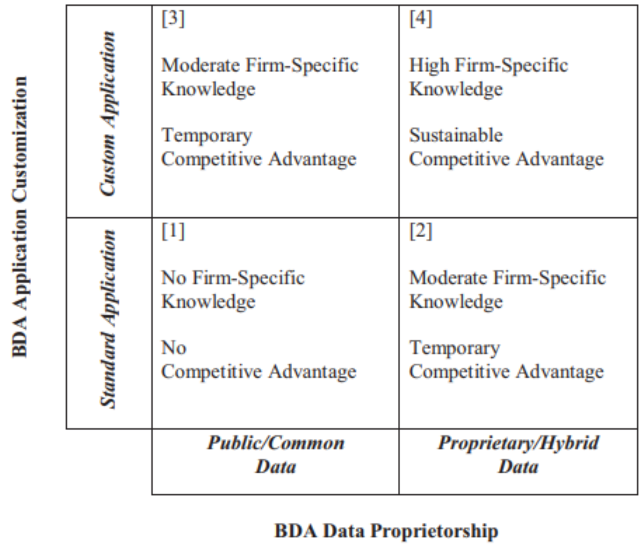

Figure 5. RBV framework of BDA (Dahiya et al. 2022)

As illustrated by Dahiya et al. (2022), the RBV is a suitable framework for interpreting the application of BDA within firms and how this can lead to sustaining a competitive advantage. The RBV and the framework of BDA firm-specific knowledge and competitive advantage by Dahiya et al. (2022) will lay the theoretical foundation for interpreting the managers' relation to BDA application and firm performance. As such, in our analysis, we will refer to this framework to interpret whether managers perceive their use of BDA to establish a competitive advantage as an indicator of increased firm performance.

When considering RBV and its application to BDA analysis, we must also include Gupta and George (2016) who describe the capabilities related to BDA as tangible, human and intangible (Figure 6). We have included this perspective particularly for the clear depiction of human capabilities and related skills. This is the theoretical foundation that allows us to connect the skills and styles of managers to their influence on the managerial utilisation of BDA.

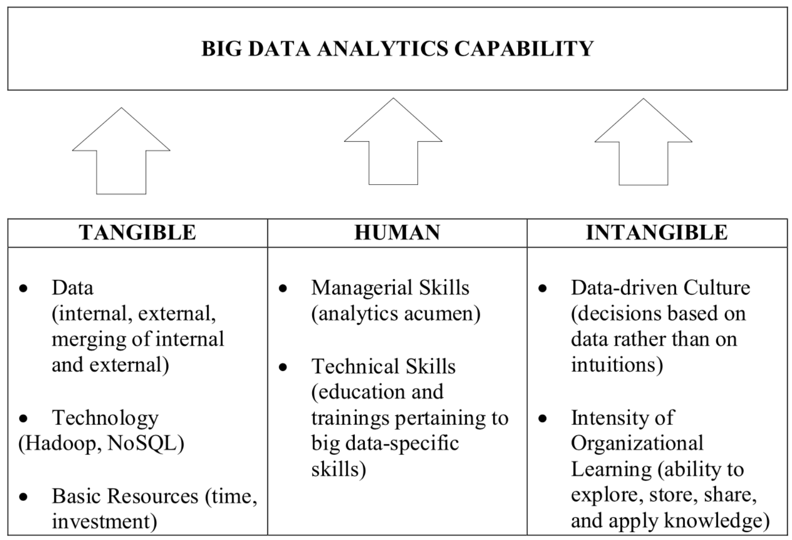

Figure 6. BDA Capabilities (Gupta & George, 2016)

3.5.2 Managerial Style and Position

Since this thesis aims to add insights into the relationship between current management and BDA, we consider managerial styles as a worthy element to analyse for managers that utilise BDA (Gupta & George, 2016). By considering human skills as one-third of a firm's resources, alongside tangible assets and intangible ones (Gupta & George, 2016), we are able to extend the discussion from previous research where managerial skills were included in the theoretical framework. However in previous research, there is only a limited focus on the manager role, and often no distinction between skills and possible managerial approaches considering BDA applications (Gupta & George, 2016). We believe that introducing Mintzberg's (2009) perspective could improve the analysis of the role of managers in BDA-related departments.

Since the aim of the study is to understand how the skills and styles of managers influence their use of BDA, the definition of style by Mintzberg (2009) was useful in adding depth to our findings. Managing style is described by the author as how managers approach their work, emphasising how managers work not what they work on (Mintzberg, 2009). The author stresses the influence of tenure and background on the managing style, which will be also reported in our analysis as related questions are a part of the interview guide. The scope of our research is to analyse personal style alongside the skills and position of the manager. Style is reported in the book “Managing” (2009) to be the approach to how managers work (Mintzberg, 2009). Analysing these items will increase the depth of understanding about managers that use BDA, through an approach that has not been used for such investigation before in this field.

Mintzberg (2009) has developed an intuitive framework to identify various management styles based on three main nodes: art, craft, and science. The science category is related to managers being deliberate and analytical whilst the art category is related to managers being visionary and intuitive in their managing style. The craft category is related to managers being practical and hands-on (Mintzberg, 2009). Mintzberg (2009) argues that managers whose style is too much of one practice are imbalanced in their management, and therefore are unable to reach optimal effectiveness. Being too much of an art, craft, or science category can lead to managers being either narcissistic, calculating, or tedious (Figure 7). Furthermore, the combination of only two managing styles without including any aspects of the third can also be problematic. Mintzberg (2009) states that a binary combination of either art, craft, or science can lead to disorganised, dispirited, or disconnected management (Figure 7).

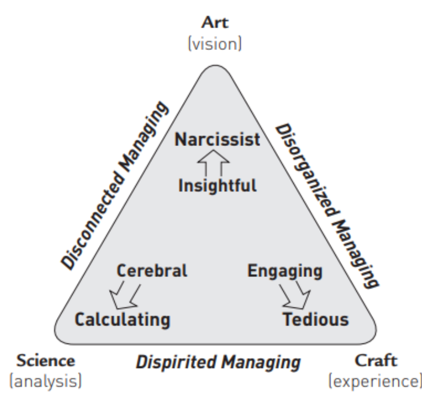

Figure 7. Styles of Managing in terms of Art, Craft, and Science (Mintzberg, 2009)

Mintzberg’s framework of the different management styles can provide insights as to how managers combine the different dimensions of managing styles to effectively go about their managerial duties. As the author states, managers seldom end up being in managerial positions by chance, and the context of their managing style may often be determined by what they face in their managing jobs. Therefore, we will adopt this framework in our qualitative research approach to add depth to our understanding of how managers use BDA to improve firm performance. It is possible to test this framework by asking the respondent to pick between three concepts, related to managerial style, which are displayed in Table 3. Each reply corresponds to points in one of the columns, which stand for the three nodes. The results are then inserted into a triangle scheme, providing an initial idea of what the management style is in relation to the three nodes (Mintzberg, 2009).

Table 3. Managing Style Test (Mintzberg, 2009)

Ideas	Experiences	Facts
Intuitive	Practical	Analytical
Heart	Hands	Head
Strategies	Processes	Outcomes
Inspiring	Engaging	Informing
Passionate	Helpful	Reliable
Novel	Realistic	Determined
Imagining	Learning	Organizing
Seeing it	Doing it	Thinking it
"The possibilities are endless!"	"Consider it done!"	"That's perfect!"

From Mintzberg (2009) we have also considered the "Perception of the place of the manager" (position of the manager) as part of the "Personal Style of Managing" section of Chapter 4. This diagram groups three different positions in which managers perceive themselves as being within the organisation. We wanted to include this as a question during our data collection, as it may shed some light on the attitude of managers towards communication, leadership and other soft skills. These soft skills are considered fundamental from previous papers (Ferraris et al. 2018; McAfee & Brynjolfsson, 2012; Mikalef, Giannakos, Pappas, & Krogstie, 2018) and yet the relationship between the manager and the team they manage has not yet been thoroughly explored. The inclusion of the scheme (Figure 8) in our data collection and analysis may therefore enrich the study, especially considering the motivation behind managers' choices over the three options and the connection between the choice of skills.

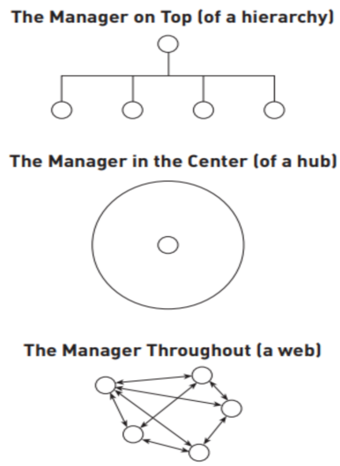

Figure 8. *Position of the Manager (Mintzberg, 2009)*

3.6 Theoretical framework

The theoretical framework seen in Figure 9, includes the main theoretical concepts we have highlighted in this chapter.

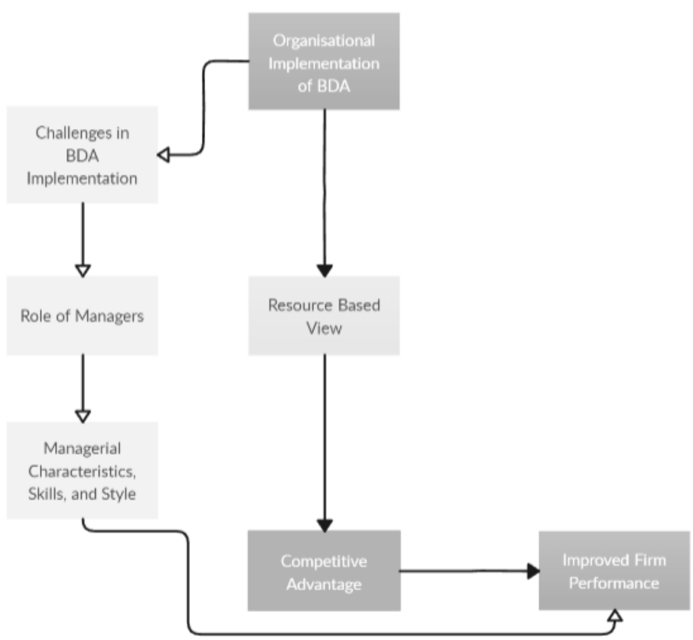

Figure 9. Theoretical framework

Considering previous literature, the framework (Figure 8) we have developed aims at identifying what role managers play in establishing a competitive advantage through the use of BDA. The framework in Figure 8 will be used in the analysis to make sense of the empirical findings by connecting elements of the framework and previous literature to the data that is presented.

We began this chapter by considering firm performance and analysing studies like Ferraris et al. (2018) and Raguseo and Vitari (2018) that establish how companies can benefit from implementing BDA in their organisation, but also establish the requirements for investments to be functional and effective. We then considered how the Resource Based View would be a useful framework to analyse BDA's impact on firm performance by considering the conditions under which a resource can establish a competitive advantage and how managers can play a key role in this context (Wang et al. 2018; Chae et al. 2014; Gupta & George, 2016; Dahiya et al. 2022). We thus considered implementing theories from Mintzberg (2009) since we noticed a literature gap over the targeted themes and identified an opportunity to sustain findings using affirmed literature that is manager centred. By adding managerial elements from the literature (Mintzberg, 2009; Ferraris et al. 2018; Hysong, 2006; Gupta & George, 2016; McAfee & Brynjolfsson, 2012) into the theoretical framework, we will also be able to deepen theoretical and practical implications of what managerial characteristics (in terms of skills and managing styles) seem to be important in implementing BDA to improve firm performance.

4. Empirical Findings and Analysis

The fourth chapter will present the empirical findings of our data collection and the analysis of these findings using a thematic analysis approach.

Based on the thematic analysis approach, we inductively identified five main themes from the coding of the data that was collected from the interviews. The final themes were:

1. Managerial Profile
2. Perceived challenges of BDA

3. Managerial skills related to BDA
4. Perceived Implications of BDA on Firm Performance
5. The future of BDA

The thematic analysis approach in this study used the approach of Braun and Clarke (2012) which followed a six-step process. The process of developing and naming the final themes started with the familiarisation of the raw data which was achieved by reading the raw data extensively. After becoming familiar with the raw data, we started coding it using NVIVO by systematically highlighting meaningful text in the form of words, sentences and paragraphs. After the coding process was concluded, we inductively searched for themes and categories by investigating potential patterns of different ideas and topics of the codes. The initial thematic categorization of the data extract of the coding is illustrated in Figure 10.

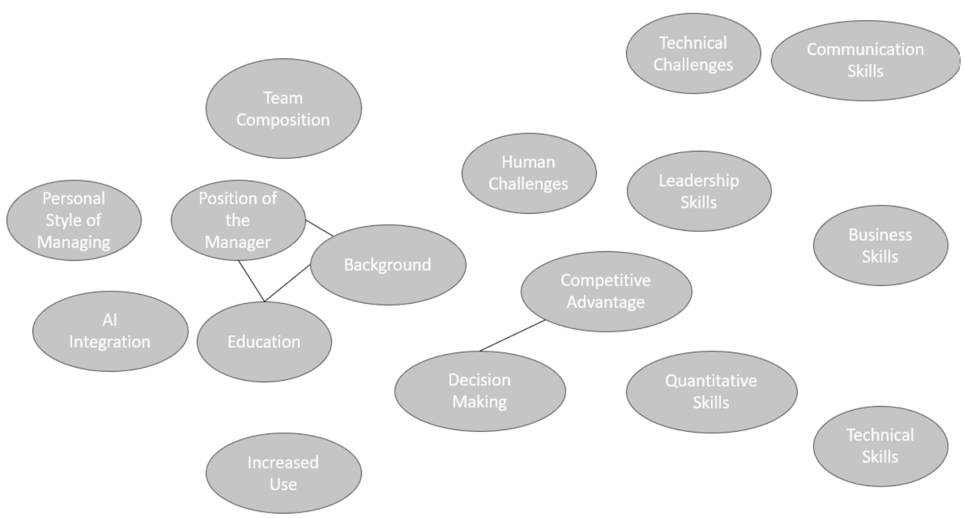

Figure 10. Categorization of codes

By reviewing the initial themes and categories, we identified the emerging relationships between the scattered themes and created main themes related to those in Figure 9. Eventually, we were able to engage in the process of evaluating the themes by considering how coherent they were in regard to their coding content. This process led us to define each main theme with a description to capture its function. This process is illustrated in Figure 11.

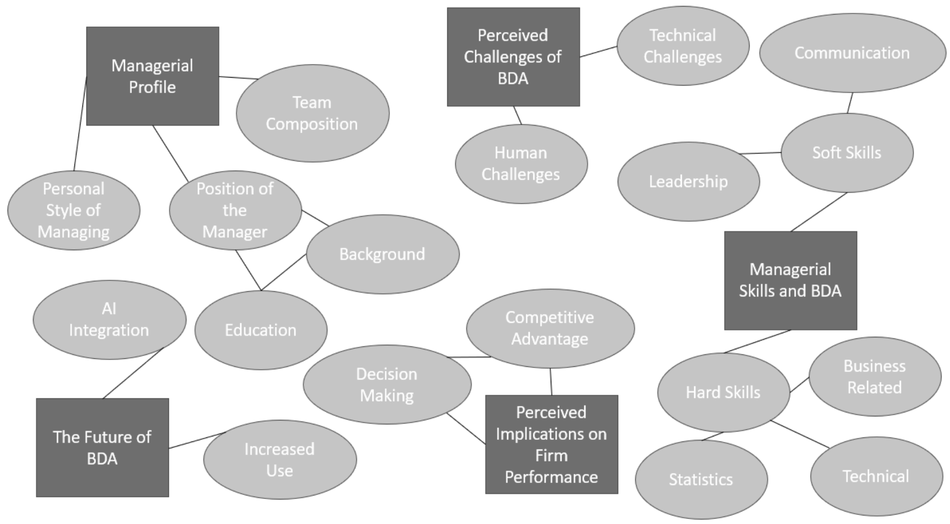

Figure 11. Initial thematic map with five main themes

Finally, in this chapter we develop the themes, exploring their narratives by quoting examples from the data, providing supportive evidence, and analysing them with support from our theoretical framework to provide meaningful insights considering the purpose of this study. As such, during the final sequence of the thematic analysis, we decided to eliminate a majority of the sub-themes as they were part of the main themes without a clear enough distinction to separate them. The final thematic map used in the analysis is illustrated in Figure 12.

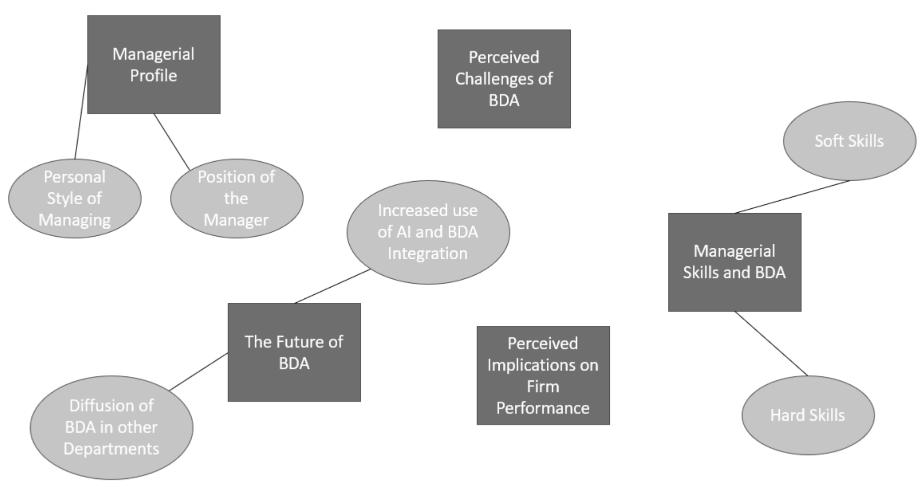

Figure 12. Developed thematic map

The first theme *Managerial Profile* is based on data which is related to the background, experience, education, managerial style, and position of the manager. This has allowed us to empirically map out the skills, styles and positions of managers which are perceived to be relevant in their understanding and use of BDA within the firms. When coding the data we decided to separate the *Personal Style of Managing* and the *Position of the Manager* into two sub-themes due to the distinction of the data. The second main theme (*Perceived Challenges of BDA*) includes the technical and human challenges that managers believe to be the most prominent in their roles when implementing BDA tools and solutions. The third main theme (*Managerial Skills*) is grouped into two sub-themes: hard and soft skills that the BDA managers perceived to be important in their role. The separation of the two sub-themes seemed necessary as the respondents distinctively separated the two when discussing this topic, which was also illustrated in most of the literature regarding managerial skills that we considered for our thesis. The fourth main theme (*Perceived Implications of BDA on Firm Performance*) includes data related to how managers implement BDA tools and solutions to establish a competitive advantage for the firm, as well as how it is used for decision-making purposes. Finally, the fifth main theme (*Future of BDA*) consists of the managers' thoughts on the future of BDA from the perspective of their own current roles as managers, gathering both their personal opinions and the possible insights they were able to disclose.

4.1 Managerial Profile

As the research pivots around the manager's skills and styles, the first theme of the managerial profile will be discussed considering the results from tests that map managerial styles, and the information coded in the interview transcripts. The intention is to refer to Mintzberg's (2009) tests as an initial indication or starting point, but mainly analyse the managerial profile from the results of interviews.

4.1.1 Personal Style of Management

Mintzberg (2009) has developed a framework to analyse managerial style as a triangle that includes art, craft and science (see Chapter 3.4.1). Considering previous literature on skills and styles adopted by managers that use Big Data Technologies, the tendency may not be pointing towards the art node, but may rather be strongly oriented towards the science node and eventually the craft node (Persaud, 2021; Ismail & Abidin, 2016). This study aims at understanding the role of managers in the correct employment of BDA. Thus, a better understanding of their managerial style can provide insights into how managers translate BDA capabilities into assets aligned with the interests and targets of a company (Ferraris et al. 2018).

In Table 4 and Figure 13, the results from the managers on the Managing Style Test are displayed. These results help us grasp what the tendencies of managers that are directly in charge of BDA are. The test was conducted without immediately showing the scheme to the interviewees, in order to not generate bias in their replies. The context and meaning of personal management style were briefly presented mentioning the sources from which this framework derives. The results from the test are enriched by the empirical findings and certain patterns that were observed in the interviews.

Table 4. Results from Respondents on Managing Style Test from Mintzberg (2009)

RESPONDENT	ART NODE	CRAFT NODE	SCIENCE NODE
R1	4	4	2
R2	2	7	1
R3	7	1	2
R4	3	2	5
R5	4	3	3
R6	5	3	2
R7	5	5	0

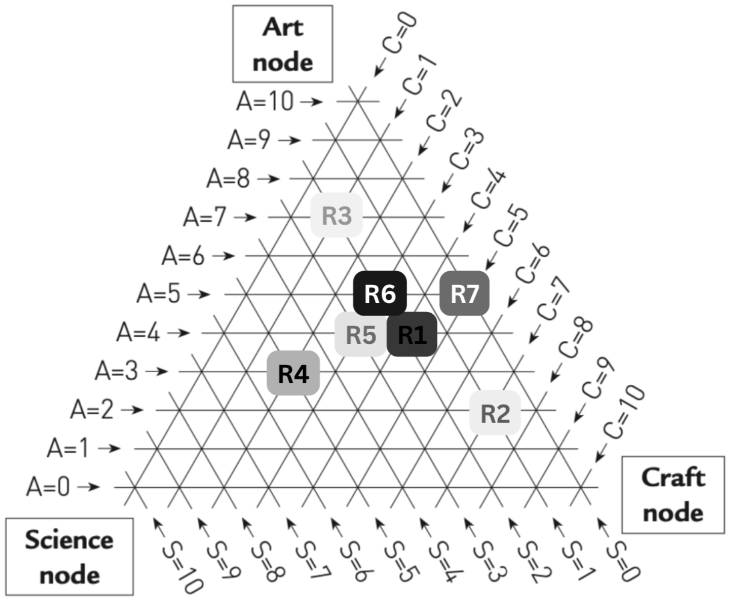

Figure 13. Illustrative results from applying the "Managing Style Test" from Mintzberg (2009)

Mintzberg (2009) suggests that the ideal management style lies in an equilibrium between the three nodes, considering that the tendency to lean more towards one corner of the triangle may negatively affect the quality of the manager. In general, the interviewee base mostly includes managers that do not tend towards any specific node.

R2 and R3 are the only two leaning more towards one node or the other showing tendencies that correspond to their respective interviews. R2 in fact stressed the importance of the technical side of the manager, admitting that a general understanding of the data structure could be insufficient for managing employees and that a thorough IT and domain knowledge (Ismail & Abidin, 2016) is necessary to be managers. R2 is a data scientist manager, reflecting the tendencies of this role to lean towards technicalities and craft, while R3 works as a cloud manager, a role that is mostly sales-related. This manager, while still having a very technical background in terms of previous experiences, possesses a double education in business and computer science. During the interview he highlighted the tendency of managing in a style that resembles the art node, as shown in how important it was for him to manage the bigger picture of the department, being more of a leader or captain directing high-skilled employees towards the firm's objectives.

Both R6 and R7 declared that oftentimes there would be a tendency to misinterpret the quantity of data or analysis needed and that managers need to balance the team in order to deliver results that are in line with their capabilities as well as requests from the firm and its clients. Replies from R3 about all the topics match his leaning towards the Art node, generally sustaining that technical abilities are important, yet it is fundamental to only recognize patterns in the data management, both to curate the product (cloud service) and to use BDA for sales purposes. For the rest of the managers, the balance between the business side and the scientific aspect of using BDA is considered pivotal for the use of such results.

Considering the three main nodes reported by Mintzberg (2009), the managers expressed their "way of managing" as generally balanced between these items. A digression towards the art node was always discouraged as it may bias the approach with the highly technical operations conducted by the teams. As reported by R3: *"You need to understand the operations conducted by your colleagues, both in terms of how much resources they need to finish a project, but also in terms of how difficult it may be"*. Many reported how important it was for them to be able to understand and eventually suggest solutions to the team, however, no interviewee declared that they needed to drastically intervene to correct or sustain certain tasks themselves. This indicates that there is a solid distance also from the craft node, as R5 explained: *"I really believe in empowering the team meaning that I will define the problem to solve but not how to solve it, it's up to the team to decide how to solve it within the constraints of the company"*.
The third node represents science and can be seen as the inclination to be analytical, which could represent a tendency for managers that cover the positions we studied (Table 2). But even if the managers reported the possibility of creating their own dashboards or performing analysis at the same level as their employees, being too fixed on an analytical mindset was regarded as a perilous tendency by R5, as it may create some distance between the firm's objectives and the department's work.

A balanced position of the manager could also mean a more central role inside the organisation. In this case, as companies become more and more data-oriented (Ferraris et al. 2018) managers that operate with BDA are more inclined to become central in the organisations' structure and more aligned with the firms' targets (Mikalef et al. 2018; Almeida & Calistru, 2013). We can observe this by considering both the results that this test presents and the information gathered during the interviews.

4.1.2 Position of the Manager

Mintzberg (2009) considers the perceived position of the manager as one of the contexts that helps define the managerial style of an individual. Since previous studies solely focused on a general level of managerial skills, without providing many insights into how the skills were used by managers (Persaud, 2021; Ismail & Adibin, 2016; Gupta & George, 2016), we decided to analyse how they position themselves to manage the use of BDA and employees that use BDA (Table 4). The classification of the position of the manager by Mintzberg (2009) allows one to understand how the manager applies certain skills in directing employees but also provides an insight into the benefits and duties of maintaining a certain position in the organisation. Results from this part can be then discussed to further develop what managerial styles are best suited for managers that use BDA, connecting also what skills are more enhanced in these professions.

Table 4. Results of respondents' self-perceived managing position from Mintzberg (2009)

POSITION (Mintzberg, 2009)	MANAGERS' PICKS
"The Manager on Top (of a hierarchy)"	0
"The Manager in a Center (of a hub)"	1 (R5)
"The Manager Throughout (a web)"	6 (R1, R2, R3, R4, R6, R7)

The most frequent choice of interviewees was the position of being included as part of a web and managing throughout this connected scheme. This position entails that managers *"suggest a favouring of linking over leading, dealing over doing, and convincing over-controlling"* Mintzberg (2009, p. 125). Being part of a web may also lead to the possibility of sharing managerial responsibilities (Mintzberg, 2009). None of the managers we interviewed selected the "Top of the hierarchy" option, motivating the choice as being too distant from their tasks and the correct approach to the team and the company. Mintzberg (2009) describes this position with the tendency of performing controls over the managed employees, which reflects our results as managers always seemed to value the empowerment of employees, the collaboration between team members and their independence.

R7 reported: "We collaborate a lot with different teams across the company. And it's always that, you know, you're trying to change minds in every conversation that you have."

Maintaining a dynamic attitude towards the position the manager holds helps our interviewees to gather information from different parts of the organisation, but also outside the organisation. The data scientist from IKEA, who held a conference at Lund University on April 26 2023, underlined the necessity to be up to date with the current research about Machine Learning and Big Data Analytics. From higher management positions, he was allowed to focus on only studying for one day of the week, in order to improve the reception of innovations and eventually transfer new knowledge into business action. As a team that works on BDA may deliver insights for other teams, being connected in a web that includes more than their own department felt like a necessity for the managers. This also allows them to have a wider understanding of all the business processes and consequent targets, from the legal departments to the marketing ones.

Only one manager chose the "Center of a hub" position. R5 chose the position of manager in the middle, as he perceives himself as an information hub that always needs to be accessible. Mintzberg (2009) underlines how this position is fundamental to be reachable for a range of activities and information, both inside and outside the organisation. The manager (R5) also highlighted the importance of learning and communicating within the team, as well as empowering employees to solve problems using their own solutions.

"I will pick the middle one, I would say I tried to take the position of a servant leader providing my team with the tools they need to do their work. But I'm also an information hub for them, and sometimes also a shield. So I shield them from noise and uncertainty and give them peace of mind to work. Or at least that's my ambition, but also to give them the tools and resources they need to do the work, make sure they are seen and have a reasonable work-life balance and so support them if something goes wrong, but maybe support against other managers or teams or stakeholders if there's something happening" - R5

The position of the manager also has importance within the entire organisation's structure. We aimed at finding out what the position of managers was considering the investment in BDA, as leaders of departments that use such instruments, and how much influence they had in the decisions related to acquiring new assets. Caesarius and Hohental (2018) report certain cases of managers that have not received enough support from the general management to proceed with certain investments they required, motivating them to consider quitting their position. In our selection of respondents we did not find such experiences, which could be connected to the great size of the companies included in this research. At the same time, we did not report any case in which the manager had the final word over investment in BDA.

We also wanted to inquire what type of employees our interviewees were managing, in order to have a more thorough understanding of the internal dynamics. Most of the teams managed by the respondents are composed of highly skilled professionals, who possess an education in data science or related fields. The education level of both the managers and the regular employees was at the Master's level, with some teams including employees who had acquired PhDs. The background also mattered, as the managers naturally developed discussions about how competent and skilled their collaborators were and how this allowed them to primarily manage them and not work as analysts themselves. R1 and R5 mentioned that they manage economists and sociologists in their teams, with the requirement of being highly skilled in statistical operations. Minztberg (2009) explains how management style can be influenced by scale and scope. Scale means the number of people in the manager's team while scope is the degree of freedom of the manager (Mintzberg, 2009). We did not aim to thoroughly analyse these aspects, but it is fair to state that the managers generally had a team that varied between 3 and 20 people with more external collaborators. The scale that managers operate in is therefore rather restricted but respondents always highlighted external inputs and how they manage the work within the team. The general situation seemed to be that of a small team but strongly competent in adapting to different needs provided by the organisation.

4.2 Perceived Challenges of BDA

The majority of the interviewed managers did express some concerns regarding the challenges of the implementation of BDA within their organisations. There was an emerging pattern of challenges that were expressed by the managers to be either technically or human-related. A common perception of a technical challenge of BDA that was shared among the managers was the issue of statistical biases and low-quality data. Similar to the proposed literature and framework (Dahiya et al. 2022; Almeida & Calistru, 2013; McAfee & Brynjolfsson, 2012), R4 emphasised how the process of selecting the data is as important as the analytics of the data. R4 argued that a main challenge of BDA is selecting the data according to what purpose the BDA solution aims at accomplishing:

"We want to be more and more data-driven, and therefore use it (BDA) in our daily decision making, so there's always a place to improve [in regards to data quality]." and *"when we receive the data, we need to make sure that it is of proper quality, not just to gather a lot of Big Data. Then, which data can we really use, that is very important. Or, should we really get data from this source or another source if it's better? And then, not basically keep the data that is unnecessarily taking up the space."*

R4 along with White (2012) stressed the issue of data quality as it is imperative for the quality of the insights that BDA can generate. R4 mentioned that a common misconception of BDA, and data analysis in general, is that quantity is preferred over quality (in terms of data volume). She stressed that this misconception has been exasperated since the emergence of BDA and the externalities of hype surrounding the topic. R1 added to this perceived challenge of low-quality data having a detrimental effect on the quality of Big Data estimates by saying: *"Low-quality data affects the estimations produced by our solutions. Biases from statistical estimates of something or whatever it may be heavy lowers the applicability of those generated insights."*

Ultimately, R4's and R1's main concerns related to data quality were synonymous with the idea of lower-quality data being negatively correlated to making profitable and rational decisions within their organisations in line with what was stated by White (2012). The issue of low-quality data seems to be linked to the challenge of being able to distinguish low-quality data from high-quality data, and how to find better sources of data when the quality of the data is too low.

Furthermore, a challenge that was mentioned by some respondents was the difficulty of enabling the team of data scientists and data engineers to create a BDA platform or solution that is able to fulfil its purpose and function. R1 said:

“There's sometimes an issue with sort of the efficiency, perhaps, sort of doing the right thing, building a Big Data analytics solution that does the thing that you actually need it to do. And that's that, that is a pretty big challenge. And I see that I play an important part in that.”

The respondents who mentioned the challenge of creating a BDA solution that is able to generate insights that are relevant to the decisions that the organisation wishes to make often expressed this concern from the perspective of their impact on this challenge. This finding can be related to the conclusions of Almeida and Calistru (2013), Ferraris et al. (2018), and Obitade (2019) regarding the intermediary role and responsibility of managers and leaders in assimilating BDA-generated insights and optimising their value. More specifically, Almeida and Calistru (2013) and McAfee and Brynjolfsson (2012) argued that managers play an important role in knowing and deciding what decisions BDA insights will inform, which is in line with the perception of R1 in the above quote. R5 also explained that an important aspect of his managerial role was to ensure that the BDA solutions generate relevant insights by saying:

“I need to manage both all the stakeholders related to our department, but I also need to understand what they actually are doing. This is so I understand how to help them. And it's when there is a mismatch between our [BDA] solution and what's actually helpful for the people on the floor making decisions, then it's that's a big risk that we build something that's not solving the contemporary issues.”

R2 added to this by saying that the perceived value of the BDA-generated insights is dependent on what type of questions stakeholders are looking to get answers to through the use of BDA. R2 stated:

"If you or the stakeholders are asking the right questions, then you will get a very good overview of the business itself. For example, why did our revenue go up this much? Or why did we lose this many clients? These insights are nice to have depending on the needs of the business."

To be able to successfully build BDA solutions that generate relevant insights, managers of BDA departments must be able to successfully communicate with different stakeholders (McAfee & Brynjolfsson, 2012; Davenport & Patil, 2012; Gong & Janssen, 2020). As stated by R5, managing the desires of stakeholders is also a difficult but important aspect of his work. R1 defined this challenge as being able to navigate nuance and being able to understand the mindsets and wishes of the different stakeholders for which his department was working. According to R1, building and extracting insights generated from BDA requires technical skills as it is rich in nuance, and communicating these insights to other departments requires communication skills. Relating to this, R1 said:

"One of the toughest challenges is making sure that you're building the right thing (the right BDA solution). One really challenging thing that I often come across is that when you build something and you dig far enough into the details, things start to become very nuanced. It's super, super important to make sure that you can navigate this nuance with what you do. Technical hard skills mean that I have some level of understanding to navigate this nuance"

In this quote, R1 expressed that the role of the manager is important in creating value through the use of BDA. This finding can be related to conclusions by Almeida and Calistru (2013), Ferraris et al. (2018), and Obitade (2021) on the intermediary role and responsibility of managers and leaders in assimilating the BDA-generated insights and optimising their value, but also the stakeholder management aspect of the literature (McAfee & Brynjolfsson, 2012; Davenport & Patil, 2012; Gong & Janssen, 2020). R1 perceived his ability to address this challenge of knowledge assimilation and transfer to be exceptionally good by being an effective communicator and possessing a higher level of technical skill than what he assumed other managers have, whilst R5 believed that being able *"to build domain knowledge very quickly, is something I find very useful."* to tackle this challenge. R5's statement aligns with the literature

(Ferraris et al. 2018; McAfee & Brynjolfsson, 2012; Ismail & Abidin, 2016) where the authors conclude that leaders who are able to build and combine domain expertise with data science are better equipped to gain a competitive advantage. This illustrates a clearly advantageous ability and attitude for managers of BDA to have.

As illustrated in one of his quotes, R1 refers to this challenge as being very nuanced. Due to his technical skill set and communication skills, R1 is able to extract relevant insights for the business and communicate these insights effectively to other stakeholders who often do not understand the technical aspects of the BDA-generated insight. As the literature (McAfee & Brynjolfsson, 2012; Davenport & Patil, 2012; Gong & Janssen, 2020) and R5, R2, and R1 stated, the challenge of stakeholder management and engagement is a crucial aspect for BDA managers and users of BDA in organisations to consider and mitigate if data-driven insights are to reach their full potential.

Unique to the other respondents and the literature that was incorporated into our theoretical framework, R7 stated that the main challenge for his team of five people was a scaling issue. We had not encountered said challenge in the literature which indicates some form of novelty of this observation, however, R7 believed that by consistently providing valuable insights into consumer and product behaviour, the issue of scalability would be resolved.

"That's something that we have in mind all the time when we work. How can we make sure that the work that we do really scales as we want to be the enabler, not the bottleneck. So that's something we have to keep in mind constantly." - R7

4.3 Managerial Skills and BDA

In this section we gather the results of our queries about managerial skills, which will be divided between soft skills and hard ones. The relevance of these findings can be included in the discussion about the influence of skills in relation to the optimised exploitation of BDA technologies, and the influence that it may bring considering the companies' tendency to become more data-driven (Tallon, Ramirez & Short, 2013; Mikalef et al. 2018). The division, as reported in Chapter 2, was structured around hard and soft skills, in order to maintain a general open definition and gather as much information as possible from the interviewees.

4.3.1 Hard Skills

It is possible to classify the main hard skills related to Big Data Analytics following the scheme provided by Ismail and Abidin (2016), which considers the relevance of three main clusters of skills: IT-related skills, Domain understanding and Data Science. In the overlapping of these areas, the essence of exploiting Big Data becomes functional for business. Additionally, Gupta and George (2016) emphasise the importance of managers having a deep understanding of the data and analytics processes as these skills exist in a symbiotic relationship with the managers' ability to communicate insights to stakeholders. During the interviews, it was possible to notice the relevant presence of all the clusters as the respondents stated what soft and hard skills they perceived to possess.

In parity with Ismail and Abidin (2016), IT-related skills were underlined by R4 as she first expressed that a solid knowledge of IT-related skills and programming was necessary to communicate with engineers. Even if she was not actively working on a certain task, the knowledge required to understand and deliberate indications implied her competence in programming. When asked if she valued technical knowledge from the perspective of a manager, R4 stated:

"In my case, yes, that's pretty much valued. And whenever it is needed, I can help our engineers. Like, okay, what is wrong? And then what can be done? How can we do it better? In the case of performance, I'm going to focus on how we can deliver better performance at a lower cost."

R2 reports similar thoughts, as for managers that directly use BDA it is necessary to express any concern regarding the whole end-to-end treatment and configuration of data. He expressed that a background in engineering is not mandatory, however, having hands-on experience can be considered as a requirement for managers. When asked about the topic of having technical skills as a manager in his position, R2 stated:

"It's easier, because you kind of understand a little bit, both in terms of how much resources you will need to finish a project and how difficult it could be. But I think also from another perspective is that if you want to kind of look further at how you design the solutions, then you need to understand a little bit about if we designed the solution this way, what future impact it can have. So, on a more long-term perspective, I would say, a background in and hands-on experience in SQL, would be very beneficial."

R1 confirmed how useful it is to have a solid knowledge of coding languages and skills, however, he did not consider the specific coding languages among the required skills for his position. There is an advantage in understanding the tasks the team has to work on, however, specific knowledge of the processes may not be required. Following this path, R3 confirmed that the specific skills can be useful to understand the team's work and provide leadership orientation towards business results, but for him, it was more important to understand mechanisms and data organisation, which is only then translated to or by the team to achieve results.

"So, I think that's a strong foundational understanding of data and data platforms, how they work, what's possible, for me is more important than Python or SQL, because that's there are tools these days that abstract the way that, you know, with wizards and dropdowns, to create that, you know, obviously, it's more powerful if you do SQL directly. But that's not the problem, I think it's more of a problem of not understanding what's possible to achieve." - R3

The clear pattern amongst the respondents was how they valued technical skill sets in their positions as managers, however, for slightly different reasons. For instance, in R4's case, she valued technical skills in her role as it enabled her to help her team to solve issues that directly relate to performance issues. In contrast, R1, R2, and R3 argued that technical skills and understanding are beneficial for leadership and understanding what the potential of their team is, and how to achieve it. R7 stated that there is not much emphasis on technical hard skills for managers of BDA as their main tasks are centred on leading and coaching people rather than engaging with the actual programming. However he did mention that being technically skilled as a manager may be beneficial nonetheless:

“It's both fun and good to kind of stay connected with the team's work to kind of keep your hands dirty a little bit, as well. But it's not the most important thing. But more importantly, having a hypothesis-driven mindset is crucial for leading a team dealing with data.” - R7

When it comes to hard skills we can refer to Ismail and Abidin (2016) and Figure 3, which reported a classification of hard skills in Statistical and Programming languages. During the interviews, the main hard skills required in the Programming part were registered as proficiency in Python, which is the most used programming language by all the teams managed by our respondents, while SQL and Java were only mentioned as secondary tools. The necessity to hold statistical skills was also highlighted during the interviews, especially skills that are related to statistical models. However, there was no precise mention of tools such as R, SPSS analysis or SAS (Ismail & Abidin, 2016).

Concerning the tools used for data management, we noticed that the hard skills were more oriented towards AWS, Google Cloud Services and DataBricks, rather than previous clouds like Hadoop, which was considered one of the main tools in previous research (George & Gupta, 2016). Hysong (2006) considers the value of hard skills as pivotal for managers that supervise technical tasks, however, there is also a requirement for business-related skills that are often considered and eventually more important to secure the correct development of business activities.

As reported by R2: *“Having just hands-on experience with querying data and visualising, it helps, it helps a little bit to understand how other businesses or your consumer wants to consume the data. I will say that it's good to have a mix. I think just having an engineering background, could also sometimes be a negative thing. Because normally, when you, in the end, deliver insights is normally to business people. And you need to kind of understand how they think. And if you only have an engineering background with a lot of coding skills, it's kind of hard to communicate effectively with a business.”*

These insights call for the examination of soft skills as well, which are reportedly combined with hard skills to reach optimum performance. However, as we expected, respondents underlined the importance of soft skills in combination with hard ones, as the second does not guarantee success in the management of employees that utilise BDA. This result matches with the ones reported by Persaud (2021), demonstrating that the exclusive possession of hard skills is not sufficient to be efficient in the management of BDA and that soft skills play a vital role for professionals in this field.

4.3.2 Soft Skills

"A lot of people come in, as managers and have a lot of hard skills and expertise. But they might not be effective as managers anyway, because they lack the knowledge or understanding on how to motivate people and how to keep talent. But I think that's true for maybe most roles where you transition from an expert role into a leadership role that you suddenly don't, you can't rely on your expertise anymore. You need a different skill set as a manager. And that's why I also say that I think the hard skills are overrated, while the soft skills are underrated. that said, we still need to understand what people are doing. Otherwise, you can't really help them out, you can't coach them, and so on. So it's too easy to say that you just need soft skills, or you need hard skills." - R5

In the interview with R5, the balance between hard skills and soft skills was reported as being pivotal while soft skills, which are often lacking in this environment according to R5, were considered pivotal. This statement is also confirmed by Mikalef et al. (2018) since respondents from their research underlined the importance of soft skills. These skills can be considered the foundation to then be able to effectively manage through hard skills and technicalities. The idea of having a balance between soft skills and hard skills as a manager of BDA was corroborated by R7 as he stressed that the ability to understand the development and data insight extraction process was crucial for him then to coach and lead his team towards improvement.

R1 considered soft skills such as communication, collaboration, and stakeholder engagement to be important skills that managers should be equipped with to successfully implement and extract value from business analytics. Other proposed literature also supports the necessity of communication skills, stakeholder engagement, and leadership skills for managers in analytics departments as the manager role often entails the management of people (Ferraris et al. 2018; McAfee & Brynjolfsson 2012). Similarly, R5 and R7 argued that leadership skills are important for managers in BDA departments as it requires them to have the ability to lead people, as relying on one's expertise is not sufficient for a managing role. Hence, R5 expressed his concern about hard skills being overrated whilst soft skills are wrongfully overlooked and neglected by managers of analytics departments. This illustrates a contradiction against most respondents as they emphasised the importance of possessing technical and hard skills in their managerial roles whilst R5 critically reflected on how soft skills are underrated and overlooked.

Furthermore, R5 conveyed his opinion on specific key elements of soft skills that are required for a person in his position to be effective. R5 went on to discuss how he valued leadership, communication, and stakeholder management skills in line with the literature (Ferraris et al. 2018; McAfee & Brynjolfsson 2012):

"how to handle stakeholders, how to communicate, how to motivate people. I think that's probably what's most undervalued in our field today. A lot of people come in, as managers and have a lot of hard skills and expertise. But they might not be effective as managers anyway, because they lack the knowledge or understanding on how to motivate people and how to keep talent."

McAfee and Brynjolfsson (2012) emphasised that a key skill that managers of analytics departments should possess is being able to be a good leader. Without it, managers are not able to align data initiatives with business objectives, cultivate data-driven decision-making amongst team members, or promote cross-functional collaboration among departments and stakeholders (McAfee & Brynjolfsson, 2012). R4 was among the respondents that stressed how leadership skills were crucial for her role. R4 expressed how she values her leadership skills as it allows her to understand what her team is doing and how to guide them towards improvement, as well as communicating with them effectively:

"Definitely leadership is the most important soft skill as I work with people that are highly technically skilled… So it's good that first of all, to sit with them, be with them and learn together with them." and *"I value being a good leader and of course, the ability to communicate things very well with them [her team]."*

The notion of communication being an important part of managers dealing with BDA has been discussed in the literature (Ferraris et al. 2018; McAfee & Brynjolfsson, 2012) and was corroborated by all respondents. R1 mentioned that communication is key in handling stakeholder management which points to him valuing communication and cross-functional collaborations as discussed by the literature (McAfee & Brynjolfsson, 2012; Ferraris et al. 2018; Davenport & Patil, 2012). R1 argued that communication with stakeholders is key when he stated:

"One of the absolute most important things is to be able to communicate and be able to say that, okay, now this is what we've done, these are the recommendations that we give, and so on and so forth. You have to be able to communicate that easily and effectively [with stakeholders]."

R3 did not explicitly mention communication as being a key soft skill to possess in his role as a manager using BDA, however, he did discuss how he valued storytelling as a soft skill. As R3 explained, being on the production and sales side of BDA tools and solutions means that being a good storyteller enables him to construct stories similar to *"movies and books"* and in the end, *"connect the dots of the story."* R3 stressed how useful storytelling is as a skill:

"And that's what you do in a customer meeting, telling them why they should choose our data platform because it will solve all the problems they have by telling that in an exciting and attractive way where everything fits together in the end." and *"you can have all the skills in the world. But if you cannot explain that or portray all your skills in a way that the customer resonates with [through storytelling], then it doesn't matter what skills you have."*

When breaking down the conversation and analysing the core of R3's thoughts, it becomes clear that R3's thoughts on storytelling revolve mainly around the ability to, essentially, communicate.

Through his thoughts on storytelling, R3's idea of effective communication was depicted very differently from the rest of the respondents. According to R3, without the ability to communicate through storytelling, it does not matter what skills you possess as you are not able to convey the valuable insights to other stakeholders that have been generated from a person's other skills, making them redundant. This perspective was also underlined by R6 but with an opposing view to that of R3. R6 emphasised how storytelling may sometimes lead to a one-sided dialogue with partners and clients. R6 argued that in situations such as sales of complex products and services, such as automation and digital solutions, storytelling may lead to the waste of potential customers' and sellers' time. The reason for this, R6 argued, was:

"Because it might be a cold case, meaning they [a customer] might like what you present, but they have no need for it, which means they will never buy it." and "*I could tell a very good story about everything, but it's not to the point, it's more relevant to understand what they would be interested in rather than being a good storyteller."*

Furthermore, R2 mentioned that having the ability to have a deeper understanding of the business that he is operating in enables him to communicate better with stakeholders. When asked what soft skills he thinks are important, R2 stated:

"In terms of soft skills, one is to understand the business needs, you need to kind of understand the business yourself." R2 argued that this allows for better decision-making at higher management as this gives him the ability to *"communicate with the business what they actually want to have because a lot of times the business itself does not really know what they want."*

4.4 Perceived Implications of BDA on Firm Performance

After interviewing all respondents, we discovered that there was a general consensus on how BDA can be applied in an organisational setting to improve firm performance. It was commonly agreed amongst the respondents that BDA is mainly used in decision-making as the insights generated from BDA can inform decision-makers on multiple levels. When exploring the perceived implications of BDA on firm performance, we aim at analysing the value of which the respondents perceive BDA-generated insights to have, and whether this contributes to establishing a competitive advantage as the previous literature that has been discussed claims (Akter et al. 2016; Alrumiah & Hadwan, 2021; Gupta & George, 2016; Obitade, 2021; Ferraris et al. 2018; Dahiya et al. 2022).

The findings of Wang et al. (2018), Chae et al. (2014), and Dahiya et al. (2022) all support the theory of the deployment of BDA capabilities in a firm increases firm performance from an RBV perspective, but they do not specify if different forms of BDA applications are more efficient than others in doing so. Dahiya et al. (2022) consider the BDA application customization in their framework, but not any specific areas of application. As most respondents argued that their firms' BDA capabilities contribute to establishing a competitive advantage in some shape or form, this created the opportunity for us to explore how their perceived implications on the matter differed depending on the type of BDA solution and application that the managers use.

As the respondents were all managers in departments with different objectives and purposes, the use of BDA within these departments differed concurrently. In line with what applications BDA may have according to Alrumiah and Hadwan (2021) and Gupta and George (2016), all respondents mentioned the predictive powers of BDA and how predictive estimations and analysis is beneficial for decision-making purposes. The predictive powers of BDA are used for internal cost and time efficiency as illustrated in R3's quote and supported by Dahiya et al. (2022), but R3 also argued that it can be used for marketing and sales purposes:

"But also you're obviously using Big Data for forecasting and doing everything from inventory forecasting to predictive maintenance. We're working with a car manufacturer in Sweden that feeds in billions of data variables every day from every robot they have in the factory to understand, you know, things like that to be able to do predictive maintenance."

R7 emphasised the critical predictive insights that BDA can generate for the department where he is a manager, namely, the electrification development department at Scania. R7's main use of BDA was the predictive insights of customer behaviour, as the development of new products often entails some sort of hypothesis of how their products will be used, and then collecting user data to understand fully how their products are being used and what can be improved for future updates. R7 called this the "development loop" and stressed that BDA plays a major role in completing it. R7 argued that BDA is a tool for Scania and his department to complete the development loop, which R7 perceived to be the biggest contributor to improving firm performance through the use of BDA. He stated:

"It's really difficult to get that full perspective [of the product] by just talking to a few customers and really understand how things are going. So today, BDA really becomes a tool for getting the full perspective and seeing kind of how the products are being used. What can we learn from the kind of the usage of the products that we see in the data? That is a critical part of the development loop." and *"Developing the right products that are tailored for a specific customer needs is key. And if we can use Big Data to get feedback from our customers, all over the world, then we can do that much better than then if we didn't have that data. So that's the main driver for gaining a competitive advantage for Scania."*

Considering the framework by Dahiya et al. (2022), R7's thoughts on the implications of BDA refer to the level of data proprietorship, meaning that exclusive access to their users' data leads to better opportunities for improved product development in the future, thus helping Scania gain a competitive advantage. R2 argued that Klarna uses BDA mostly for the purpose of targeting consumers to increase sales. However, R2 went on to say that the purpose and use of BDA in an organisation are generally heavily influenced by the type of business it is running. For example, R2 discussed how the application and design of BDA solutions are different depending on the nature of the business that the firm is operating in by saying:

"It depends on the business, like if you have a business that does have a lot of customer support, then it [BDA] will actually greatly help and indirectly affect your other parts of the business. So by analysing which clients are most likely to return a product and making predictions there, you can actually improve your margins a lot." and *" The idea of Big Data is, I think, that you want to have as many variables or parameters that you can to make predictions on."*

These statements can be connected to Dahiya et al.'s (2022) framework (Figure 4) and the concept of firm-specific knowledge and data proprietorship. Similar to what Dahiya et al. (2022) discussed, R2 stated that the larger the data sets and the more variables and parameters a firm can make predictions on, the higher the firm-specificity of knowledge from the BDA-generated insights. Therefore, the more valuable the generated predictions are in establishing a competitive advantage. Furthermore, R2 argued that larger volumes of data are a main contributor to establishing a competitive advantage through the application of BDA solutions. He gave the example that larger companies are usually in a better position to establish a competitive advantage through BDA by having access to larger datasets and more data sources. He went on by saying:

"So let's say from the perspective of Klarna, as they have a lot of users, so they can make more accurate predictions compared to maybe a similar company of a smaller size. So you have advantages in terms of the volume of the data, if everything else was the same, you have more advantages based on the volume of data."

In the case of R1, his main area of application for the BDA solutions that were used is pricing. R1 is the manager of a team that builds and uses BDA solutions to algorithmically set prices for the products and services that they offer with the aim to set the most optimal prices and gain the most profit based on consumers' price sensitivity and willingness to pay. He said:

"So for us, it's all about how accurate we can be. Right? The absolute ideal scenario is that we set a price point and create a pricing strategy that ends up with the last booking, just literally one second before the booking window closes, the last slot on the ship is booked."

In this case, R1 argued that by setting an optimal price at the equilibrium of demand and supply, the firm is able to make the most profit whilst improving customer satisfaction as the freighter is fully booked and everyone paid a price that they were willing to pay. By algorithmically setting prices based on the insights generated from BDA, R1 is able to provide the firm with better chances at achieving higher profit margins for the prices of its products and services. R1 claims that this improves his firm's performance as they receive higher profits and improve customer retention. This is in line with the findings of Alrumiah and Hadwan (2021), where BDA-generated insights allow firms to capitalise on consumer behaviour.

Being on the production and sales side of BDA, R3 stated that he mainly uses BDA internally to get insights on customers which then helps him establish better relationships with his customers whilst also being able to provide them with better services. R3 argued that these BDA-generated insights on his customers create customer loyalty and increase customer satisfaction when he said:

"I think the way we are data-driven, the customer feels we understand them, the customers feel we are close to them. And then just whenever you do have a customer meeting, you are on top of what they're doing. You know what their problems are, what their strengths are ... And so being data-informed, from a customer perspective, customers really like that you're on top of their business and that you understand their business."

R3 argued that achieving higher levels of customer satisfaction has allowed his company to acquire bigger accounts and more loyal clients. This in turn helps his company to increase firm performance as they receive bigger orders and expand their client portfolio by having the competitive advantage of being informed on their customers. R3 expressed how BDA-generated insights can both improve internal cost efficiencies but also external relations with customers, therefore illustrating the two-way benefits of using BDA to improve both the performance of internal and external components of a firm. This was in parity with R6 who believed that predictive insights generated through BDA can aid his department in suggesting machine maintenance and the sales of other products and services, whilst improving customer satisfaction and service whilst doing so. R6 stated:

"We use BDA to understand how equipment is running at customer sites, providing insights back to the customer on possible improvements." and *"We provide insights to our development organisations, so they can improve the machines and make systems better, smarter, and more efficient. So basically, reduction of cost for equipment or extending the lifetime of things that are not working or helping customers with maintenance and improving our services."*

This observation shows that the literature (Alrumiah & Hadwan, 2021; Gupta & George, 2016) on the predictive powers of BDA and the use of insights of such nature is applicable in practice. It also illustrates the two-way nature of the implications of BDA on firm performance where it can both improve market and financial performance, but also customer satisfaction.

Furthermore, R5 argued that with the development of generative AI and the exponentially increasing investments in BDA capabilities across firms, the competitive advantages once established through means of BDA solutions are ceasing to exist. According to the perception of R5, this is due to the commoditization of AI and BDA technologies. R5 stated:

"These technologies [BDA & AI] don't create any competitive advantage because they are available to everyone. So they are commoditized, they will improve everyone's performance if they learn to use it."

R5 argued that the use of BDA solutions has become a commoditized resource and standard in the general landscape of the industry in which his company is operating. Relating this to the RBV framework in Figure 4 by Dahiya et al. (2022), the BDA application customization is standard and does not contribute to a competitive advantage. As such, R5 argued that the insights or the analytical product of BDA in an organisation do not create value *per se*. However, he did argue that if used correctly, the insights generated from BDA can contribute to establishing a competitive advantage. In his thoughts, R5 argued that it was the process of how the insights generated from BDA are used that creates value internally or externally as illustrated in his quote:

"So no value is in the analytical product itself, it's the use of the analytical product that creates a competitive advantage." and *"competitive advantage can both be both in terms of providing vendors solutions for the customers, but also being more internally efficient."*

Although the BDA solution can generate firm-specific knowledge in the analytical product, R5 argued that it is worthless unless it is applied and used effectively. This corroborates the framework of Dahiya et al. (2022), where optimization of insight application or BDA application customization is crucial in terms of BDA's effectiveness in establishing a competitive advantage.

4.5 The Future of BDA

In this section we have gathered the findings regarding the future applications of BDA and the perception of managers about evolutions in this field as well as how their role could eventually change in the upcoming years.

4.5.1 Diffusion of BDA in Other Departments

Another topic that we wanted to address in the interviews, was the diffusion of BDA in other departments. Ferraris et. al (2018) discuss how the increased Data-Driven Culture in companies will lead to managers that make more use of analytics in their position to sharpen decision-making and conduct precise analysis of resources and markets. We have investigated this field with an open question, trying to gather the opinions of managers about how they have perceived this change, and how they forecast this tendency to progress. In general, the response was positive towards the implementation of data in more areas of firms, however, the replies were different on how this process will manifest.

R2 hypothesised that departments will include BDA experts in their staff, even if it is not a department that is highly influenced by the processing of data.

"I think we are moving more towards like, where, each business function will hire their own kind of data guy or data girl. So, I think all if not most of the business functions would need some kind of data expert in and they will be kind of sitting closer to the business." R2

This perspective can be considered in accordance with the view of Ferraris et. al (2018) and Barton and Court (2012) who argue that better information delivered in terms of format would benefit the company, as even those who do not possess analyst skills can benefit from the information gathered with Big Data. The possibility of deploying ad-hoc personnel that acknowledges the departments' needs and satisfies them would align with the literature just mentioned. However, another trend sees employees of different departments becoming more skilled in the use of BDA, as the only way to truly capitalise on investing in BDA assets (Shan et. al, 2012). R1 explained that considering the well-developed Data-Driven Culture of the firm he already sees this diffusion.

"There are very few teams in our company who do not use data in some form or shape. But then, of course, you could argue, what's Big Data Analytics, right? And there. Of course, you could then argue that now HR data, that's not Big Data, those are tiny, smaller data sets." R1

With similar opinion, R5 maintained that the reskilling of personnel will be a key aspect of the development of diffusion of BDA among other departments. This has also been recognized in the literature, as BDA skills are often hard to find in the job market (Gandomi & Haider, 2015; Ferraris et. al, 2017).

"No, I think academia has a real challenge here moving forward, but in order to provide people with education that is relevant on the job market has always been a challenge. That will become an even bigger challenge in the future, because of these cross-functional skills you will need to have both HR skills and technology skills. Exactly what the technology skills, or let's say the analytical skills need to be is hard to say today, because I don't think that you will need computer science skills, but you will need to have a deep understanding of analytics in order to have a successful career." R5

During the interviews it was R5 that emphasised the collaboration between the department he is managing and the data analysis done on behalf of other departments or by collaborating with them. Whether the future will present a diffuse use of BDA in departments that are not yet accustomed to it, and how will this happen, was discussed in an extensive way by respondents. Technological development is probably the most relevant variable in this context, as confirmed by R5 as well. It becomes rather hard to predict how technology will impact employees' ability to manage BDA. The diffusion and increased use of Social Media have incentivised the analysis of BDA and therefore the involvement of firms in aiming at deploying workforce to analyse such data (Gandomi & Haider, 2015). During the interviews, this process was frequently associated with the development of generative AI, which appears to be the next groundbreaking change also in firms' use of BDA.

4.5.2 Increase use of AI and BDA Integration

All respondents stressed the development of AI and the impact this will have on BDA departments in the near future. However, some differences emerged considering the timeline of when AI will make its biggest impact. A general consensus amongst the respondents was the effect that AI is expected to have on data departments in organisations, namely the increased accessibility of analytical tools and solutions. As such, the general consensus amongst the respondents was that demand for highly technically skilled data engineers and data scientists is expected to decrease in the future as more, less technically skilled, people can use analytical tools with the help of AI. Some respondents also argued that it will on the other hand increase the demand for more generalised expertise, especially in management positions where knowledge assimilation and transfer are key components for managers on top of technical knowledge.

A recent study conducted by Gandomi, Chen, and Abualigah (2023) argues that the future of integrated AI techniques in Big Data is promising as it will be automating data analysis. Gandomi, Chen, and Abualigah (2023) state that AI automation will enable organisations to generate insights in real-time and more accurately, hence, enabling organisations to be more accurately data-driven. Subsequently, organisations with AI-integrated techniques will be more competitively advantageous (Gandomi, Chen & Abualigah, 2023). In line with these predictions, R3 stated that generative AI will improve the value of BDA-generated insights whilst also decreasing the demand for technical skills of the users:

"I think this is a bit of a problem for many because you don't get the magic of Big Data that you could because it's still a bit too complex for people to get the type of insights that they want. Now, this is changing with generative AI…. And now you can almost have natural discussions with the data. This is going to change a lot in the coming 12 to 18 months when this technology makes it possible for anyone to use BDA tools." and *"It's almost as if the data you want to look at becomes a human and you can talk to it, with the help of AI."*

R1 on the other hand, was more sceptical of the perceived advancements of AIt: *"We're either overestimating the AI capabilities, or we're severely underestimating the complexities with data and data lakes."* He went on to say that the main challenge of BDA is understanding what the data means and how it can be used, stating that the development of AI is a long way away from being able to tell us the answers to these questions in a meaningful way. The general attitude amongst respondents was however optimistic as they expected the technology of the future to increase the efficiency and effectiveness of their work. R4 summarised her thoughts on the topic by saying: *"So we should just look at what technology brings for us in the future, and then learn and adapt."*

R6, in parity with other respondents, argued that there will be an increase in the use of BDA within organisations, but that it will not change much for managers other than increase efficiency. R6 had a fresh take on the topic and discussed his predictions on the future of BDA by using analogies of the emergence of previously disruptive technologies such as mobile phones and online conference calls. R6 argued that managers were able to fulfil their duties even before their employees had mobile phones or could meet with employees or clients through the web. The emergence of these technologies only increased the efficiency of organisations and managers. R6 argued that the development of BDA will be the same and said: *"BDA becomes another thing we use to do our job in a better way. So the real problem is, if you're not open and adapt to new technology, then you might fall a bit behind or you become this 'dinosaur company'."*

The British Computing Society's prediction on AI in organisations is that AI will automate certain aspects of data and software engineering roles' tasks (BCS, 2022). However, in line with the concerns of R1 and the complexity of data-related work, the BCS (2022) argues that with the emergence of AI integration and automation, other parts of the work will become more prominent. When asking R5 about his thoughts on the development of BDA, he mentioned the impact of AI, but with a completely different perception of the development timeline. R5 argued that he and his team are already exploring generative AI to an extent where he believes that it is no longer something of the future, as it is here already. Additionally, R5 argued that AI will not act as a replacement for human employees as the BCS (2022), but will rather act as an additional tool in an employee's toolbox. His position on the future of technological advancements was similar to that of R4'S as he went on to say:

"I would say already today, generative AI is helping improve my day-to-day work. I use both large language models and text to image models to help me in my daily work" and " *you won't be replaced by AI, you will be replaced by someone using AI. And I think that's probably the right way to think about this problem. It's how to leverage new technology properly."*

Following on this trend, the opinion reported during the interview with R7 presents an interesting summary of how the manager sees AI breaching into this industry:

"I think it will have a huge impact, actually, in the way that conversational AI will bridge the gap between those who need to use data. And the kind of the data itself. Even if you have the simplest of tools or platforms, there's still quite a gap between the kind of the average employee, even in an engineering organisation. That's where it's working, to actually use data for your decision making."

5. Discussion

The fifth chapter of this thesis will consist of the discussion of the findings from the analysis presented in the previous chapter. The discussion will continue to refer to our theoretical framework as we reflect on the practical implications of our findings.

Considering the theoretical framework that we constructed using elements of previous literature on the topics of management and performance implications of BDA in firms, we were able to inductively collect and analyse data from which we have presented our findings. In line with the literature, we identified key managerial challenges of BDA implementation, skills, styles, and implications of this on firm performance. Furthermore, we have inductively identified a key managerial element that was emphasised in the data, which was future predictions of BDA usage and implications within organisations. Through our analysis of the inductively identified themes and sub-themes of Figure 12, we were able to construct our final thematic map (see Figure 14). This illustrates the central ideas which are based on the three common denominators and the respectively related concepts which we inductively identified as being the centre of the respondents' thoughts and concerns.

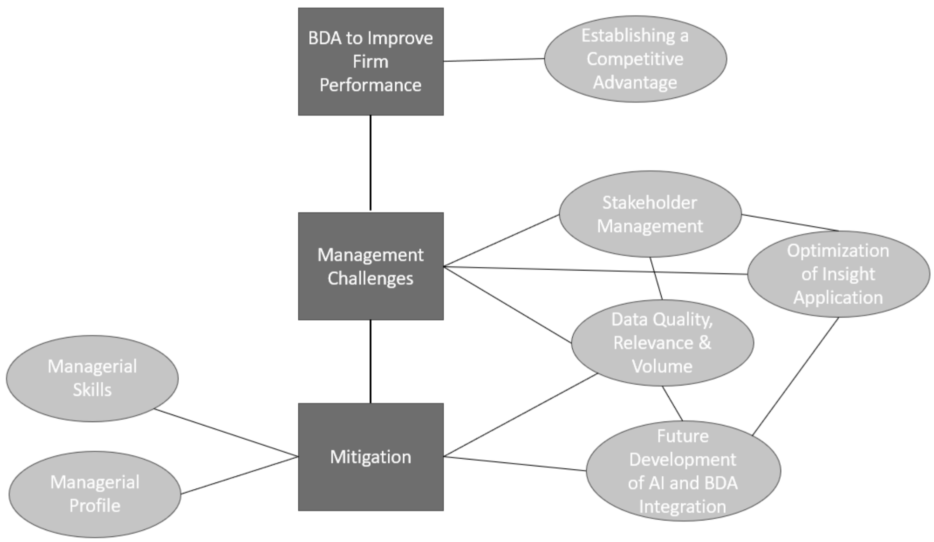

Figure 14. Final thematic map with three final main themes

In parity with the literature (Akter et al. 2016; Alrumiah & Hadwan, 2021; Gupta & George, 2016; Obitade, 2021; Ferraris et al. 2018; Dahiya et al. 2022), most respondents discussed how they are able to improve firm performance through mainly predictive analysis and gain a competitive advantage through different means. The respondents illustrated how BDA-generated insights can aid firms in improving market and financial performance, but can also improve customer satisfaction. R1, R2, and R6 discussed how predictive analytics based on Big Data can improve profitability whilst also serving customer satisfaction purposes simultaneously, whilst R3 and R7 illustrated how predictive analytics can improve sales tactics and product development through customer insights. The takeaway from analysing the findings on how the respondents use BDA to increase firm performance is based on how the respondents implied that these BDA insights aim at establishing a competitive advantage.

Although most respondents perceived the use of insights generated from BDA to aid their firms in establishing a competitive advantage in line with Dahiya et al. 2022, R5 had a contradicting view on the matter. He believed that BDA has become commoditized as a resource, therefore, recognizing that BDA is not heterogeneously distributed across competing firms. According to the principle framework of the RBV (Barney, 1991; Peteraf, 1993; Mata, Fuerst, & Barney 1995), this would entail BDA not being a viable resource to use to establish a competitive advantage. Considering that all respondents claim that they use BDA, that would also entail homogeneity of BDA as a resource across the respondents' firms. This finding, based on the respondents emphasis on the homogeneity of BDA as an asset across their industries, that BDA is not a viable asset in establishing a competitive advantage when considering the classical RBV framework (Barney, 1991; Peteraf, 1993; Mata, Fuerst, & Barney 1995).

However, considering the adoption of the BDA-adapted RBV framework of Dahiya et al. (2022) in our theoretical framework, we were able to identify how BDA can be used to establish a competitive advantage. Considering the view of R5 and other respondents, the value creation and establishment of competitive advantage through the use of BDA can be considered as the efficiency and optimization of the application of the generated insights. In parity with Dahiya et al. (2022), a key component of using BDA as a resource to establish a competitive advantage is the customization of the BDA application, being one of two determinants of whether or not BDA is a viable resource for establishing a competitive advantage. Furthermore, most respondents stressed the quality, volume, and relevance of data to be a determinant of BDA's success in improving firm performance. Consequently, considering the data proprietorship of Dahiya et al. (2022) and the quality of data concerns of White (2012), this too confirms that firm-specificity (relevance of data) is key in using BDA as a competitive resource. Upon reflection on this finding, we understand that the classical RBV framework might not be suitable for considering BDA as a viable competitive asset. However, the BDA-adapted RBV framework of Dahiya et al. (2022) does provide a suitable framework for identifying a firm's capability of establishing a competitive advantage through the firm's BDA assets.

Furthermore, the second main theme of our final version of the thematic map suggests that there are managerial challenges related to the implementation of BDA to improve firm performance.

As highlighted in our theoretical framework, we predicted that there would be challenges in implementing BDA solutions in an organisational setting. From the data, we interpreted these challenges as barriers, as the respondents presented these challenges as a form of obstacle that they, as managers, had to overcome in the implementation and generation of BDA insights. As illustrated in the literature and our theoretical framework, there are certain challenges that need to be addressed in the implementation of BDA in firms. The challenge of quality of data and risk of statistical bias (White, 2012) is thought to be a tough challenge for managers as the respondents emphasised their role in selecting the datasets that will be used in their analytics. In line with Almeida and Calistru (2013) and Gong and Janssen (2020), R4 emphasised her responsibility in disregarding data that is irrelevant as this data is likely to compromise the quality of the generated insights and take up unnecessary storage space. This, however, is contradicted by R2's thoughts on wanting to have as large of datasets as possible as he argued this to allow for more and better predictive insights. This may be a question of differences in data storage capacity as Almeida and Calistru (2013) argued was a key issue, yet it illustrates the difficulty and broad spectrum of this challenge. Based on this observation, we need to revise our theoretical framework as this result from our analysis illustrates a contradiction to the literature where future research might need to consider firms' storage capabilities as it might affect the responsibilities and required skills of managers in this setting.

The challenge of data quality, relevance, volume, and storage (Almeida & Calistru, 2013; White, 2012) seems to be connected to stakeholder management as most respondents claimed that stakeholder communication and engagement is an important factor in creating value from BDA-generated insights. This connection stems from respondents stressing how their role as BDA managers is crucial in aligning the needs of business stakeholders with the firms' BDA solutions, allowing for increased customisation of BDA applications and hence, gaining a competitive edge (Dahiya et al. 2022). This in its turn is connected to the thoughts of R5, R2, and R1 where knowing what type of insights the business stakeholders want is important for aligning BDA with all parts of a business function which are also illustrated in the literature (McAfee & Brynjolfsson, 2012; Almeida & Calistru, 2013; Ferraris et al. 2018; Dahiya et al. 2022). As managers, the respondents are responsible for the generation of these insights, but also for allowing the business to implement the BDA insights optimally if stakeholders' interests are aligned with the generated insights, corroborating the view of Dahiya et al. (2022) and the concept of BDA application customization.

Having presented the results of the managerial use and implications of BDA for firm performance, and the managerial challenges of the generation and implementation of BDA to achieve improved firm performance, we will now turn to how managers are trying to mitigate the presented challenges. We have identified key skills which the respondents perceive themselves to possess and aid them in mitigating the said challenges. As the literature used to help describe the role of the manager in our theoretical framework claims, technical, managerial, leadership and communication skills are important for managers and people of BDA and IT departments to possess (Gupta & George, 2016; Hysong, 2006; McAfee & Brynjolfsson, 2012; Vidgen, Shaw & Grant, 2017; Davenport & Patil, 2012; Mikalef et al. 2018).

As emphasised by the majority of respondents, communication skills are one of the most important skills for them as managers. Most respondents stressed that their communication skills were mostly benefiting their relationships with other business stakeholders as it enabled them to address the issue of aligning the interests of their own and other departments to allow optimal value creation through the implementation of the firms' BDA capabilities (R5, R1, R2, R4, R6). Additionally, R3 argued that communication skills in the form of storytelling serve a different purpose than stakeholder management, namely, for sales purposes. Reflecting on this, we believe the reason for this to be that R3's role was more sales-focused compared to the other respondents, meaning that the insights generated from BDA served R3 for different purposes. This skill has been seldom mentioned in the previous literature, as we can find in Ismail and Abidin (2016), but without any further investigation about what it entails. On the other hand, it is important to report how R6 saw the exacerbation of such skills, meaning that R6 explained how leaning excessively towards storytelling may be a waste of time and irrelevant to increasing performance.

Although the majority of the respondents regarded their communication skills to have the best mitigating effect to the challenge of stakeholder management and achieving optimal value creation of the BDA insights, some respondents argued that leadership in combination with communication skills is important for tackling this challenge. This observation is in line with McAfee and Brynjolfsson (2012) as they claim adequate leadership to be pivotal in choosing and aligning stakeholders' and the interests of the business whilst they also claim communication to be important in this issue, amongst other scholars (Ferraris et al. 2018; Davenport & Patil, 2012; Gong & Janssen, 2020). Ultimately, we discovered that a combination of leadership and communication skills is the most important in terms of soft skills based on these findings.

We found that leadership and communication skills are central mitigating factors in overcoming primarily challenges related to stakeholders and implementing advanced technological features such as BDA. However, this observation is not exclusive to the managerial use of BDA but can also be found in other fields such as healthcare, entrepreneurship, and education, (Chatterjee, Suy, Yen & Chhay, 2017; Men, Chen & Ji, 2021; Syakur, Susilo, Wike & Ahmadi, 2020) but also technology in organisations (Wreder, 2008). The theoretical implication of our finding of the impact of leadership and communication in technological implementation entails the consolidation and the possibility of further expanding elements of communication theories. As such, we can consolidate the idea of storytelling being an enabler of the enhancement of fostering collaboration and leading people into the future (Bolman & Deal, 2017), however, this may be contextual as our results presented opposing views on the matter. As such, storytelling can be seen as a managerial skill that can be used for selling technologically advanced products such as Big Data solutions (R3), but may also be a distraction (R6). This results in the possibility of expanding the theoretical application of communication and leadership theories to the complex integration, value extraction, and sales of BDA solutions and insights.

In extension to the soft skills that have been highlighted by the respondents, they have also discussed the importance of possessing certain hard skills. In line with Ismail and Abidin (2016), R4 highlighted how she valued technical hard skills as they assisted her in her leadership and communication skills due to her being able to lead and communicate more effectively and efficiently with her team of data engineers. This observation illustrates how hard and soft skills do not necessarily need to be considered as separate entities, but rather as two equally important and interdependent parts. R1, R2, R3, and R7 added that technical hard skills allowed them to better realise the potential of the BDA capabilities and understand resource requirements better to more effectively and efficiently fulfil that potential and maximise value creation of the insight application. The practical implications of these results warrant the interdependence of hard and soft skills of BDA managers as they each serve a purpose in fulfilling the bigger picture, which as we have observed, is the ability of managers to navigate the complexity and overcome the challenges of utilising BDA to extract and apply valuable insights which ultimately improves firm performance.

Results related to the skills can also be connected with the position of managers by Mintzberg (2009), as two out of three options were selected, with a vast majority of "Managing throughout a web", and one selection of "Managing in the centre of a hub". By positioning into a web of connections, managers are able to enhance communication and build patterns that are leading information from and towards them. This position allows managers to reach out to people that are inside or outside the team, and eventually also outside of the organisation (Mintzberg, 2009). This result can be considered valuable as it matches the skills that have been listed as important but has also an interesting side if combined with personal traits and competencies that are discussed in Persaud (2021) and Gupta and George (2016) enriching the information about how the managers actually perform in order to highlight these fundamental skills.

Additionally, the investigation of the managerial profiles of each respondent has allowed us to deepen our understanding of what type of managers are in terms of the "Personal assessment with Art, Craft, and Science" (Mintzberg, 2009). For the first test, we have derived that most of the managers interviewed maintain a stable position between the three nodes, which according to Mintzberg (2009) is a valuable way of conducting management and avoiding drifting to one node and missing out on the other two. If we compare this result with the challenges outlined by McAfee and Brynjolfsson (2012), especially considering decision-making, the company's culture, and leadership, we could conclude that the respondents are aware of the priorities in their management style, by considering the information they have disclosed during the interviews. Managers were conscious of the dangers that drifting to one direction would bring, in terms of the impact on their team and on the rest of the organisation.

We believe that the position of managers can also be connected with intangible resources such as Data-Driven Culture and Organisational Learning (Gupta & George, 2016) and with the mitigating effect of Knowledge Management of BDA reported by Ferraris et. al. (2018). As most respondents position themselves as part of a web, actively reaching for the resources they need, there could be a positive impact on the intangible resources of firms' culture about the use of BDA, which appears to be the case considering the information disclosed by the respondents considering the perceived effectiveness of collaboration between departments. The answers regarding the perceived positions of the managers were motivated matching what Mintzberg (2009) defines the positions to entail, yet we had the chance to record how the respondent summarised their choice considering the importance of communication, knowledge diffusion and constant learning. Furthermore, the respondents also valued organisational learning intended as the ability to explore, store and share knowledge within the organisation (Gupta & George, 2016), which can be facilitated as managers collaborate through an extended web (Mintzberg, 2009). This aspect also acts as mitigation for the challenges related to BDA and could be included as well in an RBV model as mitigation to some mentioned challenges were related to human resources and intangible capabilities (Gupta & George, 2016).

Even if three managers were leaning towards the Art and the Craft node or side, there were no cases of complete focus on one of the topics. We have not only considered the results of the test to draw conclusions but also noticed certain patterns about the managerial work that the managers have highlighted during the interviews. These results can be included in an RBV perspective, considering human capabilities (Gupta & George, 2016), expanding on the current evaluation of managers as part of the successful implementation and exploitation of BDA in a firm. In previous research, the role of the manager was considered fundamental for the correct use of BDA (Gupta & George, 2016; Dahiya et al. 2022; McAfee & Brynjolfsson, 2012) which our findings firmly consolidate whilst also contributing to the research of the managerial significance in effectively utilising BDA by considering specific skills, characteristics, and managing styles. We also found that managers value the relevance of their background in terms of education and previous experiences. In Mintzberg's (2009) research this was not particularly relevant, while we can suggest that for managers that need to work with BDA, this may be a strict requirement.

When considering managing style, Mintzberg (2009) also reports the importance of background. Mintzberg (2009) highlighted a collection of observations from managers that cover different roles, in different industries and countries. The background is considered slightly influential in the analysis from Mintzberg (2009), however, it is reported as significant for only six cases. In the research that we have conducted, the background (education, position, success and failure) was considered of major importance. All the interviewees (except for one) had completed an education at least to a Master's level, in subjects like physics or engineering, which are sometimes accompanied by a complementary education in business.

Furthermore, the diffusion of BDA in other departments has been addressed as an increasing trend by our respondents, matching previous literature on this topic (Ferraris et. al, 2018; Gupta and George, 2016). The replies on this topic were different between the respondents, to some (R1, R3) the diffusion of a Data-Driven Culture in their organisation is already established and multiple departments are using BDA. However, other respondents also admitted that oftentimes there is much less need for accurate analysis of Big Data in certain departments. R5 has then explained how the collaboration between the team he is managing (Data Scientists) and other teams within the company, allows them to be useful for analysis that other teams need, but do not have the in-house capabilities to perform. Furthermore, R2 assumes that eventually, departments will all include personnel that are able to perform BDA analysis, as the use of it will spread in all areas of firms.

The future development of AI and BDA integration also was presented as a promising aspect by most respondents as they predict the advancement of generative AI to simplify and increase the accessibility of BDA-generated insights in the future which is in parity with Gandomi, Chen, and Abualigah (2023). The general consensus was the prediction of a decrease in demand for technical expertise for data departments and will instead increase the demand for more generalised and broader expertise for different areas of a business. Additionally, the BCS (2022) corroborates this prediction as they argue that AI will not replace jobs within data departments, but rather change the demand for expertise. R5 argues that generative AI is already implemented in his day-to-day work and is simplifying his work as it becomes more effective and efficient.

Furthermore, R3 argues that generative AI will mitigate some of the challenges that have been suggested by the literature and the respondents within twelve to eighteen months such as the sorting and selection of data and optimising the implementation of BDA insights. However, R1 is more sceptical of the timeline of such advancements as he stresses the complexity of data and data lakes and the overestimation of the speed of AI advancements.

The impact that generative AI is expected to have according to Gandomi, Chen, and Abualigah (2023), the BCS (2022), and most respondents, makes it necessary to revise our theoretical framework. With such a big impact that generative AI is generally expected to have on BDA, it should have been considered in our theoretical framework as to how the respondents implement this groundbreaking technology to improve their efforts in improving firm performance through the use of BDA. Furthermore, it would have also been possible to include AI and machine learning skills, as well as ethics knowledge related to these fields, among the skills that managers should possess and will be increasingly required in the future, considering replies gathered from the interviews as well as recent literature like Persaud (2021). However, considering how early we are in the timeline of the development of generative AI, this may be interesting as a future line of research as will be discussed in the next section.

5.1 Limitations and future research

This section provides a summary of the research limitations and suggestions for future research. Given the evolving nature of BDA research, future research may yield different results considering the advancements in technologies such as Generative AI. Software management, task automation, and analysis accuracy are areas that are expected to change according to our respondents. Based on our interpretation of the results from our research, we suspect that managers in BDA-intense departments will remain largely unchanged. However, those who are less experienced with BDA will need to adapt to becoming more data-driven, facilitated by the progress and development of generative AI. These observations may entail that with the development of generative AI, the results from this research may become less valuable, given that the integration of AI and BDA will change the managerial aspects of BDA that have been addressed in this study.

Furthermore, an alternative research approach to that of ours may involve analysing managers from the employees' perspective and exploring similar themes. Replicating the study in different geographical locations may also yield different and insightful results as cultural variations may be an extra variable (Caesarius & Hohental, 2018). As this research focused on managerial skills and styles related to BDA and firm performance, we believe there is still an opportunity to explore other characteristics which may be difficult to capture through qualitative research. This presents the opportunity for future researchers to assess other personal characteristics such as those proposed by Persaud (2021): self-confidence, creativity, empathy, critical thinking, and curiosity through alternative research approaches. Additionally, an observational study of similar topics may provide further insight as to how managers utilise BDA to positively influence firm performance.

Finally, future research focusing on specific aspects of the management of BDA could employ quantitative methods to examine potential correlations between firm performance and specific managerial characteristics, such as those that have been examined in this thesis which can potentially add value to the insights from our research.

6. Conclusion

The final chapter of the thesis will consist of our concluding remarks and a final summary of the findings that have been presented.

In conclusion, our study successfully explored aspects of the skills, styles, and positions of managers and the implications of this on performance linked to BDA in firms. Our theoretical framework was constructed based on relevant literature which was used to analyse and interpret the empirical findings from our conducted interviews. Through the use of our theoretical framework, we identified key managerial challenges, traits relating to the respondents' managerial styles, positions, and skills and the implications of this on firm performance, and future directions for BDA. Our findings generally align with the existing literature, highlighting how BDA can improve firm performance through predictive analysis and provide firms with a competitive advantage. Although our final results consolidate the majority of the literature that has been reviewed and generally confirm the applicability of our theoretical framework (with some required revision), we still discovered some new practical and theoretical implications through our research.

While most respondents viewed BDA to be a viable resource for providing a competitive advantage, one respondent held a contradicting view, arguing that BDA had become a commoditized and homogenous resource, unable to establish a competitive advantage according to the traditional RBV theory. However, as we adopted the BDA RBV framework (Dahiya et al. 2022), we were able to consolidate the validity of the model by identifying the customization of BDA applications and the relevance of acquiring firm-specific knowledge as the determinants of BDA's ability to establish a competitive advantage for firms. Additionally, we empirically contributed to the aspect of firm-specific knowledge by linking the empirical findings on the relevance, quality, and volume of data as key contributors to increasing firm-specificity of knowledge generated through BDA.

This study also illustrates the managerial challenges in the implementation of BDA to improve firm performance. The challenges which were emphasised by the respondents were largely consistent with the literature, except for the issue of scalability. The challenges that were discussed by the respondents and highlighted in the literature included ensuring data quality, relevance, and volume, as well as stakeholder management and aligning the interests of different stakeholders with the BDA solutions, but also the ethical challenges in the use of BDA.

Regarding management style, the results that we have obtained report a high interest for managers to maintain a balance between the nodes defined by Mintzberg (2009), aligning with the previously defined importance of balancing hard and soft skills. Managers were also aware of the dangers of committing too much to one of the nodes and expressed with confidence that their position was mediating the possible tendencies of employees to focus too much on one aspect of the job. Generally, the focus was placed on leading the employees to work with data and present results that are useful to the company. Managers often gave us the impression of being guidance for these high-skilled teams, and even if they are able to perform their collaborators' tasks, their job is mainly to lead them in the right direction. We also found out how the background of managers in this sector may be fundamental, which is not often present in other managers' careers, considering Mintzberg's (2009) results.

When considering the skills which the managers believed to be important, it was emphasised that both soft and hard skills are crucial and exist harmoniously as they are used for overcoming managerial challenges and becoming effective BDA managers. The literature, as well as the respondents, deemed communication skills to be essential for stakeholder management, whilst leadership skills complemented communication skills when aligning stakeholders' interests with the BDA solutions and insights as well as leading and creating optimal circumstances for the teams to perform. This relationship between communication and leadership has been extensively highlighted in other fields of academia, however, this thesis provides a contributing element to the applicability of such concepts to the field of research regarding BDA and similar technological applications in firms. Furthermore, an interesting relationship was highlighted when certain respondents discussed the purpose and importance of their technical skills where technical skills were valued for aiding the managers in effectively leading and communicating with their teams and stakeholders to maximise the value creation of BDA. This illustrated a supporting relationship between the technical hard skills and the soft skills, where the technical hard skills complemented stakeholder management and soft skills of communication and leadership specifically.

When considering the future of BDA, many respondents reported an increasing trend where BDA being adopted in other departments was becoming more frequent, and the respondents also stressed their concerns and excitement about the future of AI integration in BDA technologies. The most common predictions were that generative AI would simplify and increase the accessibility of BDA tools and solutions and also aid in the application of the generated insights as AI is expected to do this more effectively and efficiently. This aligns with the literature on the topic of AI and BDA integration, where the demand for technical expertise will diminish and the demand for generalised knowledge and skills on a broader spectrum of a business will increase. However, some optimism was also expressed in AI's ability to help mitigate in the near future some of the challenges that the respondents and the literature have discussed. Although most respondents reported general optimism about the future capabilities of AI, one respondent believed that the modern advancements of AI are overestimated and should not be expected to be useful in the near future. Another respondent believed that the use of generative AI to aid in the mitigation of some of the challenges is already here in the present.

In conclusion, our study has provided insight into the managerial and performance implications of BDA in firms and underscores the importance of certain managerial skills and managerial styles in overcoming the managerial challenges of BDA and improving firm performance by establishing a competitive advantage, considering the use of BDA. Our empirical contributions consist mainly of the extending contribution to the framework of Dahiya et al. (2022), the illustration of the interdependence between technical hard skills and the soft skills of communication and leadership of managers, and by qualitatively deepening the mainly quantitative empirical literature on how managers in firms use BDA to increase firm performance and how the profiles of managers (style, position, skills) influence this phenomenon.

7. References

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, Available online: https://www.sciencedirect.com/science/article/pii/S0925527316302110 [Accessed 29 April 2023]

Alles, M.G., & Gray, G.L. (2016). Incorporating big data in audits: Identifying inhibitors and a research agenda to address those inhibitors, *International Journal of Accounting Information Systems*, Vol. 22, pp. 44-59

Almeida, F., & Calistru, C. (2013). The main challenges and issues of big data management. *International Journal of Research Studies in Computing*, Available online: https://www.researchgate.net/publication/272696610_The_main_challenges_and_issues_of_big_data_management [Accessed 2 May 2023]

Alrumiah, S. S., & Hadwan, M. (2021). Implementing Big Data Analytics in E-Commerce: Vendor and Customer View, Available online: https://www.researchgate.net/publication/349741121_Implementing_Big_Data_Analytics_in_E-Commerce_Vendor_and_Customer_View [Accessed 12 May 2023]

Assensoh-Kodua, A. (2019). The resource-based view: a tool of key competency for competitive advantage, *Problems and Perspectives in Management*, Available online: https://www.researchgate.net/publication/335080997_The_resource-based_view_a_tool_of_key_competency_for_competitive_advantage [Accessed 3 May 2023]

Balcar, J. (2016). Is it better to invest in hard or soft skills?. *The Economic and Labour Relations Review*, Vol. 27, no. 4, pp.453-470, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 23 April 2023]

Bharadwaj A.S. (2000). A resource-based perspective on information technology capability and firm performance: an empirical investigation, *MIS Quarterly,* Vol. 24, no. 1, pp. 169–196, Available online: https://www.jstor.org/stable/3250983 [Accessed 28 April 2023]

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage, *Journal of Management,* Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 8 April 2023]

BCS. (2023) Will AI replace software engineers?, British Computer Society (BCS), Available online: https://www.bcs.org/articles-opinion-and-research/will-ai-replace-software-engineers/ [Accessed 15 May 2023]

Bogner, W. C., & Thomas, H. (1994). Core competence and competitive advantage: A model and illustrative evidence from the pharmaceutical industry, G. Hamel & Heene (Eds.), Competence-based competition, John Wiley & Sons

Bolman, L.G., & Deal, T.E. (2017). Reframing organizations: Artistry, choice, and leadership, John Wiley & Sons

Braun, V., & Clarke, V. (2012). Thematic analysis, *APA handbook of research methods in psychology, Vol 2: Research designs: Quantitative, qualitative, neuropsychological, and biological,* Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 11 April 2023]

Bryman, A., & Bell, E. (2015). Business research methods, Oxford university press

Caesarius, L.M., & Hohenthal, J. (2018). Searching for big data: How incumbents explore a possible adoption of big data technologies, *Scandinavian Journal of Management*, pp.129-140

Cao, Min., Chychyla, R., & Stewart, T. (2015). Big data analytics in financial statement audits. *Accounting Horizons,* Vol. 29, no. 2, pp. 423-429, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 12 April 2023]

Chae, B., Sheu, C., Yang, C., & Olson, D. (2014). The impact of advanced analytics and data accuracy on operational performance: a contingent resource-based theory (RBT) perspective, *Decision Support Systems,* Vol. 59, pp. 119-126, Available online: https://www.sciencedirect.com/science/article/pii/S0167923613002595 [Accessed 2 May 2023]

Chatterjee, R., Suy, R., Yen, Y., & Chhay, L., (2018). Literature review on leadership in healthcare management. *Journal of Social Science Studies*, Vol. *5*, pp.38-47, Available online: https://www.vumc.org/faculty/sites/default/files/Healthcare%20Leadership%20Review.pdf [Accessed 20 May 2023]

Chen, C.P., & Zhang, C.Y. (2014). "Data-intensive applications, challenges, techniques and technologies: A survey on Big Data", *Information Sciences*, Vol. 275, pp. 314-347, Available online: https://www.sciencedirect.com/science/article/pii/S0020025514000346 [Accessed 15 May 2023]

Dahiya, R., Le, S., Ring, J.K., & Watson, K. (2022), "Big data analytics and competitive advantage: the strategic role of firm-specific knowledge", *Journal of Strategy and Management*, Vol. 15 No. 2, pp. 175-193, Available online: https://www.emerald.com/insight/content/doi/10.1108/JSMA-08-2020-0203/full/html?casa_token=gemE3dqpDm8AAAAA:qlqcsUfrdhFgvXz08Ws-oh6z0NQheTiiONfzv8uj7Yqn-HS9jUwXrfJdkFRzS1DqhQwojU-8kWAZ8HTkz_2rGOm3mPYTVKfRtKdr2oikFJfwmKyT8vpDDA [Accessed 29 April 2023]

Davenport, T.H., & Patil, D.J. (2012). Data Scientist: The Sexiest Job Of the 21st Century, *Harvard Business Review*, Vol. 90, no. 10, pp. 70–76, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 24 April 2023]

Dubey, R. and Gunasekaran, A. (2015), "Education and training for successful career in big data and business analytics", *Industrial & Commercial Training*, Vol. 47, pp. 174-181.

Elgendy, N., & Elragal, A. (2014). Big Data Analytics: A Literature Review Paper, *LNCS,* Vol. 8557, pp. 214-227, Available online: https://link.springer.com/chapter/10.1007/978-3-319-08976-8_16#citeas [Accessed 13 May 2023]

European Science Foundation (2017). The European Code of Conduct for Research Integrity (Revised Edition), Available online: https://www.allea.org/wp-content/uploads/2017/05/ALLEA-European-Code-of-Conduct-for-Research-Integrity-2017.pdf [Accessed 23 April 2023]

Ferraris, A., Mazzoleni, A., Devalle, A. & Couturier, J. (2019). Big data analytics capabilities and knowledge management: impact on firm performance. *Management Decision*, Vol. 57, no. 8, pp.1923-1936

Gandomi, A. H., Chen, F., & Abualigah, L. (2023) 'Big Data Analytics Using Artificial Intelligence', *Electronics,* Vol. 12, no. 4, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 15 May 2023]

Gandomi, A.H., & Haider, M. (2015). "Beyond the hype: Big data concepts, methods, and analytics", *International Journal of Information Management*, Vol. 35 no. 2, pp. 137-144.

Gong, Y., & Janssen, M. (2020). Roles and Capabilities of Enterprise Architecture in Big Data Analytics Technology Adoption and Implementation, *Journal of Theoretical and Applied Electronic Commerce Research,* Vol. 16, pp. 37-51

Groves, R.M., & Kahn, R.L. (1979). Surveys by Telephone: A National Comparison with Personal Interviews, *Academic Press*, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 11 April 2023]

Gupta, M., & George, J.F. (2016). Toward the development of a big data analytics capability. *Information & Management,* Vol. 53, no. 8, pp. 1049–1064, Available online: https://www.sciencedirect.com/science/article/pii/S0378720616300787?casa_token=9dsymZOUxOUAAAAA:6KywwtvywkQVVGSjW0fN33ijdvCxRfyYcc70SPz3pa2nKZ7QWkMAZGU1I2RZDbvXwUVadK5H0AK_ [Accessed 3 May 2023]

Hysong, S.J. (2006). The role of technical skill in perceptions of managerial performance. *Journal of Management Development*, Vol. 27, no. 3, pp. 275-290

IBM. (n.d.) "Big Data Analytics", Available online: https://www.ibm.com/analytics/big-data-analytics [Accessed 14 April 2023]

Ismail, N.A., & Abidin, W.Z. (2016). Data scientist skills, *IOSR Journal of Mobile Computing & Application*, Vol. *3,* no. 4, pp. 52-61

Johnson, J.L., Adkins, D., & Chauvin, S. (2020). A review of the quality indicators of rigor in qualitative research, *American Journal of Pharmaceutical Education*, Vol. 84, no. 1

Locke, E.A. (2007). The case for inductive theory building, *Journal of Management*, Vol. 33, no. 6, pp. 867-890

LCIA (2012). Big data: big opportunities to create business value. Available online: http://poland.emc.com/microsites/cio/articles/big-data-big-opportunities/LCIA-BigData-Opportunities-Value.pdf [Accessed 29 April 2023]

Maheshwari, S., Gautam, P., & Jaggi, C.K. (2021). Role of Big Data Analytics in supply chain management: current trends and future perspectives, *International Journal of Production Research*, Vol. 59, no. 6, pp. 1875-1900, Available online: https://www.tandfonline.com/doi/full/10.1080/00207543.2020.1793011?casa_token=erqUnaKKt2gAAAAA:C3a7a4Ms-27nZr_nDrmh54HPLBdtDyBr-bN-tFLFSeHgCJ_q52BGLTrrmehxMKclkbGVJoDPWhakFIw [Accessed 20 April 2023]

Maritz, J., Eybers, S., & Hattingh, M. (2020). Implementation considerations for big data analytics (BDA): A benefit dependency network approach, *Responsible Design, Implementation and Use of Information and Communication Technology,* Vol. 12066, pp. 481-492, Available online: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7134384/ [Accessed 28 April 2023]

Mata, F.J., Fuerst, W.L., & Barney, J.B. (1995). Information technology and sustained competitive advantage: A resource-based analysis. *MIS Quarterly*, Vol. 19, no. 4, pp. 487-505, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 18 April 2023]

Maxwell, J.A. (2013). Qualitative research design: An interactive approach, Sage

McAfee, A., & Brynjolfsson, E. (2012). Big Data: The Management Revolution, *Harvard Business Review*, Vol. 90, no. 12, pp. 16–17, Available online: https://hbr.org/2012/10/big-data-the-management-revolution [Accessed 11 May 2023]

Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Information technology and organizational performance: An integrative model of IT business value, *MIS Quarterly*, Vol. 28, no. 2, pp. 283-322

Men, L.R., Chen, Z.F., & Ji, Y.G. (2021). Cultivating relationships with startup employees: The role of entrepreneurs' leadership communication, *Management Communication Quarterly*, Vol. *35*, no. 4, pp. 518-545

Miles, M. B., & Huberman, A. M. (1994). Qualitative Data Analysis: An Expanded Sourcebook, Sage Publications

Mikalef, P., Giannakos, M.N., Pappas, I.O., & Krogstie, J. (2018). The human side of big data: Understanding the skills of the data scientist in education and industry, *2018 IEEE global engineering education conference (EDUCON)*, pp. 503-512

Mintzberg, H. (2009). Managing. Pearson Education

Monroe, B.L. (2013). The five Vs of big data political science introduction to the virtual issue on big data in political science political analysis, *Political Analysis*, Vol. 21, no. 5, pp. 1-9

Nowell, L. S., Norris, J. M., White, D. E., & Moules, N. J. (2017). Thematic Analysis: Striving to Meet the Trustworthiness Criteria, *International Journal of Qualitative Methods*, Vol. 16, no. 1, Available online: https://journals.sagepub.com/doi/pdf/10.1177/1609406917733847 [Accessed 13 April 2023]

Obitade, O. P. (2021). The mediating role of knowledge management and information systems selection management capability on Big Data Analytics quality and firm performance, *Journal of Decision Systems,* January 2021, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 10 May 2023]

Persaud, A. (2021). Key competencies for big data analytics professions: A multimethod study, *Information Technology & People*, Vol. 34, no. 1, pp.178-203

Peteraf, M.A. (1993). The cornerstones of competitive advantage: A resource-based view. *Strategic Management Journal*, Vol. 14, no. 3, pp. 179-191, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 24 April 2023]

Queirós, A., Faria, D., & Almeida, F. (2017). Strengths and limitations of qualitative and quantitative research methods, *European Journal of Education Studies*, Vol. 3, no. 9, pp. 369-387

Raguseo, E., & Vitari, C. (2018). Investments in big data analytics and firm performance: an empirical investigation of direct and mediating effects, *International Journal of Production Research*, Vol. 56, no. 15, pp. 5206-5221

Sagiroglu, S., & Sinanc, D. (2013) Big data: A review. *2013 international conference on collaboration technologies and systems (CTS),* pp. 42-47, Available online: https://academics.uccs.edu/~ooluwada/courses/datamining/ExtraReading/Big_data_A_review.pdf [Accessed 3 May 2023]

Salazar, M.K. (1990). Interviewer bias. How it affects survey research, *AAOHN Journal*, Vol. 38, no. 12, pp. 567-572

Saunders M., Lewis P., & Thornhill, A. (2009), Research Methods for Business Students, 5th edition, Financial Times Prentice Hall

Sekaran, U., & Bougie, R. (2016). Research Methods for Business: A skill building approach, 7th edn, Chichester: John Wiley & Sons

Syakur, A., Susilo, T.A.B., Wike, W., & Ahmadi, R. (2020). Sustainability of communication, organizational culture, cooperation, trust and leadership style for lecturer commitments in higher education, *Budapest International Research and Critics Institute-Journal (BIRCI-Journal)*, Vol. *3*, no. 2, pp. 1325-1335

Tallon, P. P., Ramirez, R. V., & Short, J. E. (2013). The information artifact in IT governance: toward a theory of information governance, *Journal of Management Information Systems*, Vol. 30, no. 3, pp. 141-178

Thyer, B. (2010). The Handbook of Social Work Research Methods, Sage Publications

Verma, S., & Bhattacharyya, S.S. (2017), “Perceived strategic value-based adoption of Big Data Analytics in emerging economy: A qualitative approach for Indian firms”, *Journal of Enterprise Information Management*, Vol. 30, no. 4, pp. 536-559

Vidgen, R., Shaw, S., & Grant, D.B. (2017). Management challenges in creating value from business analytics, *European Journal of Operational Research*, Vol. 261, no. 2, pp. 626-639

Wang, Y., Kung, L., Wang, W.Y.C., & Cegielski, C.G. (2018). An integrated big data analytics-enabled transformation model: application to health care. *Information & Management*, Vol. 55, no. 1, pp. 64–79

Watt, D. (2007). On Becoming a Qualitative Researcher: The Value of Reflexivity, *Qualitative Report*, Vol. 12, no. 1, pp. 82-101

White, M. (2012). Digital workplace: vision and reality, *Business Information Review*, Vol. 29, no. 4, pp. 205-214

Woiceshyn, J., & Daellenbach, U. (2018). Evaluating inductive vs deductive research in management studies: Implications for authors, editors, and reviewers, *Qualitative Research in Organizations and Management: An International Journal*, Vol. 13, no. 2, pp. 183-195

Wreder, Å. (2008). How leadership and new technology influence the work environment: experiences taken from Swedish organizations, Doctoral dissertation, Luleå University of Technology, Available online: https://www.diva-portal.org/smash/get/diva2:1077682/FULLTEXT01.pdf [Accessed 20 May 2023]

Appendix 1

Contact email to interviewees

To XX,

We are two master's students from the Master in Management programme of Lund University, and we are currently writing our thesis about the use of Big Data Analytics in firms. We aim at observing specifically the position of managers in the implementation of BDA for improving performance.

We are contacting you since the scope of our research covers managers from firms located in Scandinavian countries. Since we aim at investigating what is the role of managers in BDA implementation, it would be very helpful if you participate anonymously in this study with an interview, or eventually suggest someone that would meet our requirements and be able to participate.

The duration of the interview will be around 30 minutes, and the script with all the questions, derived from our interview guide, will be available to you before the interview. Once the data is collected we will analyse the results of the interview and send you the entire transcription, to make sure that everything reported is supervised by you. Once the thesis is completed and we receive clearance from our lecturers, we will also provide you with a copy of the complete study. For any eventuality, we can also agree to sign non-disclosure agreements and at your request provide a letter of recommendation by our supervisor, prof. Daniel Hjorth.

We are absolutely flexible when it comes to the format of the interview, as we intend to conduct them through Zoom, phone or eventually face-to-face if the venue is easily accessible for us. We are also flexible when it comes to the time and schedule of the interview, you can decide to talk to us whenever it is convenient.
Considering your role, we would gladly appreciate your participation in this study, however, we fully understand if you do not agree to commit.

Kind regards,
Lorenzo Clavarino, Oliver Bailey

Appendix 2

INTERVIEW GUIDE

This thesis aims at understanding the role of managers and their use of BDA to improve firm's performance, therefore, we would like the interviewee to always answer the questions from their own perspective as a manager. The target is to provide empirical data that considers the managerial role in improving firm performance through BDA, yet we do not aim at obtaining any private information that could either affect the company or the interviewee.

INTRO AND PRESENTATION

- Short explanation of the research and general introduction
- Short presentation of the interviewee
- Short presentation of the company and the industry in which it is operating

BDA

- How are you utilising BDA in your role as a manager?
- How many people work in the department? What is their background?
- Are you personally using any BDA tools?
- Are you managing employees that use BDA tools?
- Do you think that a thorough understanding of these tools from the position of the manager is important?
- Do you conduct all the BD operations in-house or do you outsource certain operations?
- Do you see managers in other departments becoming more inclined to develop BDA knowledge?
- What are the challenges of utilising BDA from your perspective as the manager?
- What do you consider to be the most important skills related to your role as a BDA manager?
- Do you examine the current status of BDA assets and invest consequently? Are you directly involved in the decisions about these investments?
- Do you hire people according to their BDA-related skills? Do you have teaching programs to update the personnel regarding those skills?

BDA and Performance Implications

- What is your perceived value of the insights gained from BDA?
- Can BDA be used to gain a competitive advantage?
- Does the company have any industry-unique BDA assets that leads to competitive advantage (you don't need to tell us which)? What is your role as a manager in utilising these assets?

Market & Financial Performance/Customer Satisfaction

- Would you consider the utilisation of BDA, from your perspective and from the perspective of the organisation as a whole, to either have the most impact on market & financial performance or customer satisfaction? Please elaborate.

Future use of BDA

- Can you see BDA being used more in the future of the company? How will these changes affect your role as a manager using BDA?
- Do you think more departments will use BDA for their day-to-day operations?
- What characteristics do you think future managers will need to acquire regarding BDA?
- Is there anything else you would like to add?

Thank you for participating in this study!